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GLOBAL UNCERTAINTY

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Global Uncertainty*

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Abstract

We estimate a novel measure of global financial uncertainty (GFU) with a dynamic factor framework that jointly models global, regional, and country-specific factors. We quantify the impact of GFU shocks on global output with a VAR analysis that achieves set-identification via a combination of narrative, sign, ratio, and correlation restrictions. We find that the world output loss that materialized during the great recession would have been 13% lower in absence of GFU shocks. We also unveil the existence of a global finance uncertainty multiplier: the more global financial conditions deteriorate after GFU shocks, the larger the world output contraction is.

Keywords: Global Financial Uncertainty, dynamic hierarchical factor model, structural VAR, world output loss, global finance uncertainty multiplier.

JEL codes: C32, E32.

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1 Introduction

> *"While all of the recessions since 1985 have had financial origins, the Great Recession was by far the biggest of these. [...] The Great Recession was indeed marked by a high level of uncertainty. [...] The Great Recession was also exceptionally global in nature."*

[Serena Ng and Jonathan H. Wright, *Journal of Economic Literature*, 2013]

The COVID-19 pandemic has put under the spotlight the dramatic economic effects of large global shocks, as it happened for the Global Financial Crisis and the Great Recession that followed. The Great Recession was global in nature, and it was characterized by a substantial amount of financial market uncertainty in most countries. To examine the effects of such large scale shocks, this paper proposes a novel measure of global uncertainty, which we term "global financial uncertainty" (GFU henceforth), and quantifies the world output loss due to GFU shocks during and in the aftermath of the Great Recession.[1] We do so by proceeding in two steps. First, we estimate a global financial uncertainty factor via a dynamic hierarchical factor model (DHFM) à la Moench, Ng, and Potter (2013) with data for 42 countries belonging to five continents, which account for 83% of the world output. The model is estimated on monthly volatility data over the sample July 1992 - May 2020. Monthly realized volatilities are constructed starting from daily data on stock market returns, exchange rate returns, and 10-year government bond yields. Our dataset features over 38,000 financial volatility observations at a monthly frequency.[2] Given the rich geographical coverage of our dataset, which includes heterogeneous countries and regions, we jointly model factors at different geographical levels (global, regional, country level) to minimize the risk of attributing spurious dynamics to our global factor. To estimate the DHFM model with an unbalanced panel, we extend the estimation algorithm proposed by Moench,

[1] Our estimated Global Financial Uncertainty measure, the data used in this analysis, and the Matlab codes to replicate our results are available at https://sites.google.com/site/efremcastelnuovo/home .

[2] Following Bloom (2009) and Baker, Bloom, and Terry (2020), this paper treats realized volatility as a proxy for uncertainty. The use of realized volatility, as opposed to implied (ex-ante) volatility, is due to data availability, because there are just a few implied-volatility indices available as far as the countries in our dataset are concerned. Importantly, these two concepts display a strong correlation at a monthly level - for instance, the correlation between realized and implied financial volatility in the US over the 1992M7-2020M5 sample, which is the one we focus on in this study, is 0.90. For a paper documenting the role of realized volatility (and left skewness), as opposed to uncertainty, as a driver of the business cycle, see Berger, Dew-Becker, and Giglio (2020).

Ng, and Potter (2013) by exploiting the approach of Banbura and Modugno (2014) for extracting factors from datasets with missing observations.

In the second part of our investigation, we estimate a VAR model which includes our GFU measure and two state-of-the-art measures of global financial and real activity indices, i.e., the global financial cycle proposed by Rey (2018) and Miranda-Agrippino and Rey (2020) (GFC), and the world industrial production index (WIP) estimated by Baumeister and Hamilton (2019). We interpret the former measure as a first-moment financial cycle which helps us separate GFU shocks from first-moment financial shocks, while WIP is the variable we use to proxy global output and compute the world output loss realized during the Great Recession and due to GFU shocks. A challenge we face is that of identifying GFU shocks. We do so via a novel combination of narrative, sign, ratio, and correlation restrictions, which is designed to tackle the challenging task of identifying second-moment (uncertainty) shocks separating them from first-moment financial shocks (Stock and Watson (2012)). Following Ludvigson, Ma, and Ng (2019b), we use narrative restrictions and identify key dates, corresponding to large jumps in GFU, in which financial markets were particularly volatile at a world level.[3] We impose sign restrictions on our VAR impulse responses to sharpen the identification of GFU shocks and separate them from global financial shocks and "output" shocks. As in Furlanetto, Ravazzolo, and Sarferaz (2019) (who work with US data), we disentangle first and second moment global financial shocks by imposing sign restrictions on the ratios of the GFU and GFC impulse responses to their respective shocks, i.e., we require a GFU (GFC) shock to increase (decrease) the on-impact response of the GFU/GFC ratio. Finally, Miranda-Agrippino and Rey (2020) and Baumeister and Hamilton (2019) identify, respectively, monetary policy shocks originating in the US (Miranda-Agrippino and Rey (2020)) to be relevant drivers of the global financial cycle, and oil supply shocks (Baumeister and Hamilton (2019)) of world output. To minimize the risk of confounding GFU shocks with US monetary policy and oil supply disturbances, we require our GFU shocks to be orthogonal to them. Following the indications by Lenza and Primiceri (2020), we exclude COVID-19 observations from our analysis to avoid biasing our impulse responses, which would otherwise be heavily distorted by the few COVID-19-related outliers at the end of the sample.

Our main results are the following. First, our estimated GFU factor spikes in cor-

[3] Antolín-Díaz and Rubio-Ramírez (2019) propose a narrative-based approach to identification that differs from Ludvigson et al.'s (2019) among many dimensions. We discuss these two approaches in Section 2.

respondence of well-known episodes of global financial volatility. Examples of such episodes include the collapse of the European Monetary System in 1992; the Asian and Russian crises in 1998; the 9/11 terrorist attacks in 2001; the second Gulf War in 2003; the collapse of Lehman Brothers and the onset of the Global Financial Crisis in 2008; the Greek crisis in 2010; the Eurozone sovereign debt crisis in 2011; the Chinese stock market turmoil in 2015; the Brexit referendum in 2016; and the COVID-19 pandemic shock. Second, GFU is highly correlated with regional uncertainty in North America and Europe and financial uncertainty in the US, the UK, and Germany. We interpret this evidence as supportive of the influence that "hegemons" such as these three countries have on their own regions in first place, but also at a global level. GFU turns out to be correlated also with financial uncertainty in a region like Oceania and a country like Australia. We interpret this evidence as pointing to the financial openness of the economies "down-under", which make them susceptible to financial volatility shocks originating elsewhere. Third, we find our GFU measure to be much less correlated with financial uncertainty in Asia and Latin America and in their respective countries, or in countries like China, Japan, Singapore, Italy and Greece. We interpret this evidence in favor of the ability of our model to identify financial volatility shocks due to specific events that had a particularly strong effect at a local or regional level such as the economic reforms that generated uncertainty in China in the early 1990s, currency crisis (the Peso crisis in Argentina and Mexico and the exchange rate crisis in Italy in the early 1990s; the Asian crisis triggered by the collapse of the collapse of the Thai baht in 1997), and debt crisis (Greece at the beginning of the 2010s). While these events are found to be relevant also at a global level (according to our GFU measure), our factor model points to a relatively stronger impact at a regional and country-specific level. We see this evidence as supportive of estimating a multi-level factor framework. Finally, we show that our measure of GFU comoves with other measures of financial uncertainty (such as the VIX and the proxy for financial uncertainty recently proposed by Ludvigson, Ma, and Ng (2019b)), as well as with some estimates of global macroeconomic uncertainty by Redl (2017), Mumtaz and Theodoridis (2017), and Carriero, Clark, and Marcellino (2018). The degree of correlation with these measures is high, and both ours and theirs feature the global maximum during the Great Recession. However, the pairwise correlation between GFU and these measures is clearly below one. Strikingly, no correlation is found with other measures of global uncertainty or risk such as the global economic policy uncertainty index proposed by Baker, Bloom, and Davis (2016) and Davis (2016), the world uncertainty index proposed by Ahir, Bloom, and

Furceri (2018), and the geopolitical risk measure put forth by Caldara and Iacoviello (2018). We interpret this evidence as pointing to a genuinely new information on global uncertainty carried by our GFU proxy.

Our VAR analysis points to GFU shocks as having a negative impact on both the global financial cycle and global output, with a (median) contribution to global financial cycle's volatility at business cycle frequencies of about 30%, and to that of global output of about 9%. Focusing on the Great Recession and its aftermath, our results point to a substantial role played by GFU shocks in affecting the level of world industrial production. According to our simulations, the loss in WIP during the 2008M9-2012M12 period would have been 13% lower had GFU shocks been absent. This estimate is the median value of a distribution (due to the different set of identified models) consistent with a 4%-27% range. The heterogeneity of moments associated to such models, which are all consistent with the data, can potentially enlighten us on the channels that are responsible for the transmission of GFU shocks to the real side of the economy. One of these channels is linked to the financial loss during the Great Recession as captured by the effects of GFU shocks on the global financial cycle. When putting together such loss with that of world industrial production mentioned above, we find a positive correlation between the two, i.e., models pointing to a relatively high (low) WIP loss due to GFU shocks also point to a relatively high (low) disruption of the global financial cycle. This correlation is consistent with the "finance-uncertainty multiplier" hypothesis - i.e., financial frictions acting as a magnifier of the real effects of uncertainty shocks - put forward by Gilchrist, Sim, and Zakrajšek (2014), Alfaro, Bloom, and Lin (2019), and Arellano, Bai, and Kehoe (2019). Our empirical evidence suggests that a finance-uncertainty multiplier may very well be at work at a global level. Our analysis, conducted with world-level data, also confirms previous indications coming from analysis conducted with US data, i.e., the severe business cycle effects of financial uncertainty shocks during recessions (Caggiano, Castelnuovo, and Groshenny (2014), Caggiano, Castelnuovo, and Figueres (2017)) and when conventional monetary policy actions are impeded by the zero lower bound (Caggiano, Castelnuovo, and Pellegrino (2017)). Finally, our analysis, which focuses on the role that second-moment financial shocks play at a global level, complements the one by Ha, Kose, Otrok, and Prasad (2020), who find evidence in favor of spillovers from financial cycles (as opposed to macro cycles) to the macroeconomic cycle.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the econometric model. Section 4 documents the data and the estimated global, regional, and country-specific uncertainty measures, and discusses the relation of our measure of global uncertainty with alternatives provided in the literature. Section 5 presents our structural VAR-based analysis. Section 6 concludes.

2 Related literature

Our paper contributes to the flourishing literature on the relationship between uncertainty and the business cycle in several respects (for surveys, see Bloom (2014) and Castelnuovo (2019)). Our empirical findings on the recessionary effects of uncertainty shocks at a global level support the predictions of models featuring either external uncertainty shocks hitting open economies (Benigno, Benigno, and Nisticò (2012), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Born and Pfeifer (2014), Mumtaz and Theodoridis (2015), Handley and Limão (2017), Chatterjee (2019)), or global volatility shocks (Gourio, Siemer, and Verdelhan (2013)). Macroeconomic (as opposed to financial) global factor models to estimate the macroeconomic effects of uncertainty shocks have recently been proposed by Berger, Grabert, and Kempa (2016,2017), Mumtaz and Theodoridis (2017), Redl (2017), Miescu (2018), Carriero, Clark, and Marcellino (2018), Ozturk and Sheng (2018), Mumtaz and Musso (2019), Carriero, Corsello, and Marcellino (2019), and Dibiasi and Sarferaz (2020). Our focus on financial uncertainty, as opposed to macroeconomic uncertainty, is justified by the recent empirical evidence for the US showing that uncertainty stemming from financial markets is likely to be an exogenous and relevant driver of the business cycle (Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), Ludvigson, Ma, and Ng (2019b), Fernández-Villaverde and Guerron-Quintana (2020)).[4] Our focus on financial uncertainty is also justified by the monthly frequency of the financial volatility data we work with, which allows our GFU measure to capture uncertainty spikes that lower frequency data would not necessarily detect, and that are likely to be informative for the identification of uncertainty shocks.

Our identification strategy, which features narrative restrictions identified with large realizations of global financial uncertainty shocks (on top of sign and correlation restrictions), is closer in spirit to the one proposed by Ludvigson, Ma, and Ng (2019b) than to that popularized by Antolín-Díaz and Rubio-Ramírez (2019). The latter paper proposes

[4] The debate on financial vs. macroeconomic uncertainty as drivers of real activity in the US is a still open one. For a contribution pointing to macroeconomic uncertainty as exogenous to the US business cycle, see Carriero, Clark, and Marcellino (2019).

an identification strategy that requires the contribution of a given shock in a given date to the forecast error variance of a given variable to be "overwhelming", or "the most important", or the "least important" among the shocks in the system. We follow Ludvigson et al.'s (2019) approach for two reasons. First, such approach tackles the issue of identifying uncertainty shocks, which is what we do in this paper too (domestic in their case, global in ours). A second reason is internal consistency, i.e., the global financial uncertainty factor is estimated following a frequentist strategy, and we want to do the same to identify the global effects of our global financial uncertainty shocks in our VAR investigation. Differently, the approach pursued by Antolín-Díaz and Rubio-Ramírez (2019) is proposed within a Bayesian context.[5]

Elaborating on the country-specific economic policy uncertainty indices constructed by Baker, Bloom, and Davis (2016), Davis (2016) proposes a global economic policy uncertainty (GEPU) index based on keywords in selected newspapers, while Ahir, Bloom, and Furceri (2018) perform textual analysis conditional on the Economist Intelligence Unit country reports. The latter paper also performs a panel VAR analysis, and finds that shocks to their world uncertainty index (WUI) foreshadow significant declines in global output. In a follow-up analysis, Ahir, Bloom, and Furceri (2021) find that uncertainty originating in the US and the UK has significant spillover effects at a world-level. Caldara and Iacoviello (2018) construct a geopolitical risk (GPR) index by searching selected keywords in leading international newspapers published in the US, UK, and Canada. Then, they conduct a VAR analysis on US data and find an increase in GPR to induce a persistent decline in a battery of real activity indicator. Moving to a different type of data, Ozturk and Sheng (2018) employ information on forecasters' disagreement to construct monthly measures of global macroeconomic uncertainty. With respect to these papers, we: i) focus on a different global uncertainty concept, which is, financial uncertainty; ii) employ a novel identification scheme to gauge the world output effects of uncertainty shocks; iii) conduct simulations to quantify the role of GFU shocks during and right after the Great Recession.

More closely related to our work, Kang, Ratti, and Vespignani (2017), Bonciani and Ricci (2018), and Cesa-Bianchi, Pesaran, and Rebucci (2018) construct model-based measures of global financial uncertainty. Kang, Ratti, and Vespignani (2017) and Bonciani and Ricci (2018) apply principal component analysis to extract a measure of global financial uncertainty from a dataset of stock market volatilities for 15 OECD

[5] For papers identifying uncertainty shocks at a country-level with the approach proposed by Antolín-Díaz and Rubio-Ramírez (2019), see Redl (2020) and Caggiano, Castelnuovo, Delrio, and Kima (2021).

countries, and of about 1,000 financial stock prices, respectively. Cesa-Bianchi, Pesaran, and Rebucci (2018) propose a multicounty FAVAR model with stochastic volatility to estimate quarterly measures of global macroeconomic and financial uncertainty from a dataset comprising output growth and equity market volatilities for 32 advanced and emerging economies. Our work adds to these contributions under several respects. First, unlike Kang, Ratti, and Vespignani (2017) and Bonciani and Ricci (2018), we explicitly consider a multi-layer factor structure, which covers a larger number of countries and accounts for country and region-specific dynamics. Second, relative to Cesa-Bianchi, Pesaran, and Rebucci (2018), we use a more comprehensive financial indicators dataset and conduct a structural analysis of the effects of financial uncertainty shocks that allows us to disentangle first and second moment shocks without taking any stance on exogeneity or endogeneity of uncertainty relative to the business cycle.

Our dataset is unbalanced. From a methodological perspective, we combine the algorithm for the estimation of the dynamic hierarchical factor model (DHFM) model by Moench, Ng, and Potter (2013) with the one proposed Banbura and Modugno (2014), which is designed to estimate factor models on data sets with arbitrary pattern of missing data. The DHFM offers two main advantages in our context. Relative to alternatives such as Kose, Otrok, and Whiteman (2003, 2008), the hierarchical structure it features implies a set of restrictions on its coefficients which makes it a more parsimonious model to estimate (see Del Negro and Schorfheide (2011)). As stressed by Moench, Ng, and Potter (2013), a distinctive feature of the DHFM model is that the transition equations for the factors at each level have time-varying intercepts that depend on the factors at the next higher level. Second, and again thanks to its hierarchical structure and the implied restrictions, our model estimates proper regional and country-specific factors. Differently, Kose et al.'s (2003, 2008) framework estimates regional factors that are uncorrelated with the global factor, something which renders their interpretation less immediate.

3 Data and econometric framework

3.1 Data

We download daily data on stock market returns, exchange rate returns, and 10-year Government bond yield returns for 42 countries for the period July 1992 - May 2020 from Datastream.[6] The focus on these three financial indicators is justified by the following considerations. Stock market volatility has been argued to be an empirically informative proxy for uncertainty (Bloom (2009), Leduc and Liu (2016)), and it has been theoretically linked to second-moment shocks to the discount factor of households, a shock able to generate real effects due to channels such as precautionary savings, precautionary labor supply by consumers, and upward pricing bias by firms (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Basu and Bundick (2017)). Exchange rate uncertainty has been empirically and theoretically shown to be a relevant driver of the optimal currency portfolio formation by investors, with consequences for the business cycle (Benigno, Benigno, and Nisticò (2012), Gourio, Siemer, and Verdelhan (2013)). Uncertainty surrounding bond yield returns is naturally linked to the issue of public debt sustainability, which is once again related to portfolio choices and precautionary savings (Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Blanchard (2019)).[7]

The data refer to 42 countries, which account for about 83% of world GDP in 2019 (measured in PPP) and cover five regions (North America, Latin America, Europe, Asia, and Oceania). Table 1 reports the list of countries. We move from daily returns to monthly volatilities by computing the latter as follows. Let x_{rcntd} be the raw observation of region r, country c, variable n, month t, and day d. Define daily stock market and exchange rate returns as $ret_{rcntd} \equiv \ln x_{rcntd} - \ln x_{rcnt(d-1)}$, and Government bond yields as $ret_{rcntd} \equiv x_{rcntd}$. Then, the monthly realized volatility of variable n for country c belonging to region r at month t is given by

$$\widetilde{Z}_{rcnt} = \sqrt{\frac{1}{M_{rcnt} - 1} \sum_{d=1}^{M_{rcnt}} \left(ret_{rcntd} - \overline{ret}_{rcnt} \right)^2} \tag{1}$$

where M_{rcnt} indicates the number of observations of variable n for country c belonging to region r available in month t, and the month-specific mean $\overline{ret}_{rcnt} = \frac{1}{M_{rcnt}} \sum_{d=1}^{M_{rcnt}} ret_{rnctd}$. The month-specific mean is handy to control for large swings in financial returns that

[6] Exchange rate data refer to the nominal bilateral exchange rate against the US dollar for all the non-US countries, and to the nominal major currency index for the US. These choices are justified by the role played by the US dollar as the dominant currency on the global markets (Gopinath, Boz, Casas, Díez, Gourinchas, and Plagborg-Møller (2020)).

[7] We prefer to include long-term interest rate than short-term ones due to the materialization of the zero (or effective) lower bound in a number of countries in our database during the Great Recession and the COVID-19 one. Information related to financial volumes (credit, money, leverage) would obviously be valuable as well. Unfortunately, data limitation prevents us from including this information in our dataset.

occurred during extreme events such as the global financial crisis or the COVID-19 pandemic. Monthly volatilities $\widetilde{Z}_{rcnt}$ are then standardized to obtain the zero mean, unit standard deviation observables Z_{rcnt}, which are used to estimate our factor model. While being able to have access to the three financial series mentioned above for most countries, our dataset does not comprise 10-year Government bond yields (again, at a daily frequency) for Argentina and three Asian countries (Honk Kong, Pakistan, and Philippines). It should be noted that not for all available series we have all observations spanning the July 1992 - May 2020 sample. Our unbalanced panel features 122 series for a total of 37,710 observations.[8]

Figure 1 (upper panel) plots the volatility of stock market returns for selected countries from 1992 to 2020.[9] In correspondence of the GFC and the explosion of the COVID-19 pandemic, all volatilities series spike upward simultaneously. Their average pairwise correlation is 0.44. The evidence in Figure 1 points to the possibility of a global component in financial volatility. At the same time, when looking at these data, one can appreciate the importance of modelling regional and country-specific dynamics. Figure 1 (bottom panels) displays selected pairwise correlations. Stock market volatilities in the US and Canada, both countries belonging to the same region (North America), are highly correlated, possibly because of the role of the US economy as "hegemon" in the region, or more broadly in international financial markets. Despite being significantly positive, the correlation between the US and Greece is weaker than the US-Canada one, indicating that for Greece regional or country-specific factors may also be at play. This becomes even more evident when looking at the low correlation the US and China stock market volatilities, which clearly points to the existence of important country-specific components.[10] We take this evidence as supportive of a multi-level factor approach featuring global, regional, and country-specific components.

[8] A balanced dataset conditional on 42 countries, three volatility series per country (financial volatility data on stock prices, exchange rate returns, and Government bond yields), and 335 observations per series (the number of months in the July 1992-My 2020 sample) would feature 42,210 observations. Hence, the missing obsevations we have to deal with are 4,500 (42,210-37,710).

[9] The volatility series used in our empirical exercise are available upon request.

[10] The practically absent correlation of the volatility of the American and Chinese stock market returns is driven by the period pre-WTO accession by China in December 2001, during which China was mostly hit by idiosyncratic shocks. It is important to stress that our empirical analysis refers to average facts in our investigated sample.

3.2 Econometric framework

We model our measures of financial volatility with the dynamic hierarchical factor model (DHFM hereafter) proposed by Moench, Ng, and Potter (2013). As anticipated in Section 2, this approach is more parsimonious than alternatives (e.g., Kose et al. 2003, 2008) in that it features coefficient restrictions due to its hierarchical structure, and it allows for the estimation of regional and country factors *per se* (as opposed to the regional and country-specific components that are orthogonal to the global one). Further discussions on this approach vs. alternatives can be found in Del Negro and Schorfheide (2011) and Moench, Ng, and Potter (2013)).

As above, let Z_{rcnt} be the monthly volatility at time t for variable n and country c belonging to region r, where Z_{rcnt} is mean zero and standardized to have unit variance. Then the four level factor model is given by

$$\begin{aligned} Z_{rcnt} &= \lambda^{n}_{C,rc}(L)\, C_{rct} + e_{Z_{rcnt}} \\ C_{rct} &= \Lambda_{R.rc}(L)\, R_{rt} + e_{C_{rct}} \\ R_{rt} &= \Lambda_{GFU.r}(L)\, GFU_t + e_{R_{rt}} \\ \Psi_{GFU}(L)\, GFU_t &= e_{GFU_t} \end{aligned} \tag{2}$$

where GFU_t is the common factor, $\Lambda_{GFU.r}(L)$ is the distributed lag of loadings on the common factor, $e_{R_{rt}}$ is the region-specific variation, R_{rt} is the $(k_R \times 1)$ vector of region-specific factors, where k_R denotes the number of regions, $\Lambda_{R.rc}(L)$ is the distributed lag of loadings on the region-specific factors, $e_{C_{rct}}$ is the country-specific variation, C_{rct} is the $(K_{Cr} \times 1)$ vector of country-specific factors, where K_{Cr} denotes the number of countries in region r, $\lambda^{n}_{C,rc}(L)$ is the distributed lag of loadings on the country-specific factors, and $e_{Z_{rcnt}}$ is the series specific variation. The hierarchical model in eq. (2) is such that only the country-level factors appear in the measurement equation (first row in eq. (2)). The country factors evolve according to a factor model where the common components are the regional factors and, in turn, the regional factors evolve according to a factor models where the common component is the world factor.[11]

It is important to notice that GFU_t, R_{rt}, and C_{rct} are not assumed to be orthogonal. In model (2), country-specific uncertainty measures C_{rct} are correlated with their own region-specific component R_{rt} and, in turn, the region-specific uncertainty measures

[11] Our Appendix rewrites the DHFM model presented here to put in evidence that, as pointed out by Moench, Ng, and Potter (2013), the transition equations for the factors at each level feature time-varying intercepts that depend on the factors at the next higher level.

R_{rt} are correlated with the global uncertainty component GFU_t. Moreover, variables (stock market, exchange rate and bond yield volatilities) within a country are correlated because of the region-specific factors R_{rt} or the country-specific variations $e_{C_{rct}}$, and variables within a region are correlated because of the common factors GFU_t or the region-specific variations $e_{R_{rt}}$. As anticipated in Section 2, the bottom-up approach by Moench, Ng, and Potter (2013) pursued here, which explicitly estimates the factors at each level, enables us to estimate factors whose interpretation is somewhat natural, given that also the regional and country-specific factors are not forced to be orthogonal to the global one. Differently, the approach by Kose, Otrok, and Whiteman (2003, 2008) yields block-level components that are, by construction, orthogonal to the global one.

Moench, Ng, and Potter (2013) develop an MCMC algorithm to estimate the DHFM above with a balanced panel of data. In order to handle an unbalanced panel like ours, we combine their algorithm with the EM approach proposed by Banbura and Modugno (2014). Essentially, Banbura and Modugno's (2014) idea is to write the likelihood as if the data were complete (which is what Moench, Ng, and Potter (2013) assume), and to "fill in" the missing data with steps which involve the use of the Kalman smoother and multivariate regressions. There are two main reasons why the Banbura and Modugno (2014) approach is particularly well suited in our case, where we both have a block structure and a dataset for a large number of countries with series of different sample length. First, the modified EM algorithm is computationally feasible, unlike other ML-based approaches. Second, it allows to impose restrictions on the parameters, which are needed in the case of a factor model with a block structure like ours. Applying the Banbura and Modugno (2014) algorithm allows us to obtain initial estimates of the global, the regional, and the country-specific factors from our unbalanced dataset. These estimates are then used as initial conditions in the MCMC algorithm, to obtain the posterior estimates of the factors of interest, which we interpret as our measures of global, regional, and country-specific uncertainty indices. A detailed explanation of our estimation approach is provided in the Appendix.

4 Global Financial Uncertainty

4.1 GFU

Figure 2 plots our estimated global financial uncertainty (GFU) index. A few considerations are in order. First, the index peaks in correspondence of well known historical episodes that have triggered stock market volatility in most countries in our dataset, notably: the European Monetary System collapse in 1992, the Asian crisis in 1997, the Russian crisis and the LTCM default in 1998, 9/11, Gulf war II, the US sub-prime mortgage default rate rise, the global financial crisis, the Greek debt crisis and the subsequent Eurozone crisis, the Chinese stock market turmoil, the Brexit referendum in 2016, and the COVID-19 pandemic. Second, these peaks do not originate, at least directly, in the US economy only, and can be referred in fact to different regions and countries in our panel. This is to say that this index is not a US-only index, but it instead picks up episodes of financial turmoils all around the world. Third, the index behaves similar to other volatility indices (as the US VIX) in that it features peaks that are basically never followed by realizations significantly above the mean: financial uncertainty spikes up, but then reverts quickly to the pre-shock mean.

It is of interest to compare the GFU series with three other financial indicators recently used or proposed by the literature. Figure 3 (upper panel) plots our GFU proxy, the VIX (one of the most popular measures of financial uncertainty in the literature), the US financial uncertainty index by Ludvigson, Ma, and Ng (2019a), and the global financial cycle produced by Miranda-Agrippino and Rey (2020).[12] Ludvigson et al.'s (2019) US financial uncertainty factor is the time-varying volatility of the one-step ahead forecast errors related to 148 monthly financial series and computed over the period 1960-2020.[13] Differently, Miranda-Agrippino and Rey (2020) compute a factor with a principal component approach on 1,002 series of asset prices traded on all the major global markets, a collection of corporate bond indices, and commodities price series over the sample 1990 to 2019. They find that such global financial factor (GFC) explains about 20% of the variance in the data. It is immediate to notice that all these measures comove. But how strongly correlated are they? Figure 3 (bottom panels) proposes scatterplots in a pairwise fashion. The GFU index correlates positively with all three measures, pretty strongly with the VIX (0.86) and the Ludvigson et al.'s (2019) US financial uncertainty index (0.68). Given the dominant role played by the US economy in the world financial markets, this is possibly not a surprise. GFU also correlates with the GFC factor, but the degree of correlation is much lower (0.33).[14]

[12] The last three indices are normalized to have the GFU's mean and variance. The global financial cycle (GFC) index has its sign flipped to ease comparisons – so that an increase in GFC can be interpreted as a deterioration of global financial conditions.

[13] The financial uncertainty series is available at https://www.sydneyludvigson.com/data-and-appendixes .

[14] The correlation with the original, unflipped series of the global financial cycle would obviously be -0.33.

This points to the possibility of separately isolating GFU and GFC shocks, an issue we deal with in the next Section.

How does the GFU index relates to other measures of global uncertainty proposed by the literature? Figure 4 (upper panel) plots our GFU index against six different measures of global uncertainty/risk: Davis' (2016) measure of global economic policy uncertainty (GEPU, constructed with a text search-approach following the lead by Baker, Bloom, and Davis (2016)), the world uncertainty index (WUI) measure by Ahir, Bloom, and Furceri (2018), and the geopolitical risk (GPR) index by Caldara and Iacoviello (2018), all constructed by using text as data (newspapers' as for GEPU and GPR, Economist Intelligence Unit country reports' as for WUI); as well as Redl's (2017), Mumtaz and Theodoridis' (2017) and Carriero, Clark, and Marcellino's (2018) measures of global macro uncertainty. Carriero, Clark, and Marcellino (2018) estimates of global macroeconomic uncertainty. The degree of correlation between GFU and these last three measures of macroeconomic uncertainty is high, ranging from 0.59 to 0.71. Notably, both our and their measures peak in correspondence of the Great Recession. However, the macro measures display less distinct peaks with respect to our financial volatility series, a difference which is justified by the slower-moving behavior of macroeconomic indicators with respect to financial ones. A very different picture emerges when we compare our GFU measure with the text-based ones. Strikingly, a pretty low correlation is found here, with GEPU correlating 0.14 with our measure, and WUI and GPR basically zero. This is in part due to the fact that GFU features its global maximum during the Great Recession, while the text-based measures do not; that the newspaper-based uncertainty has gradually taken off since 2016, while GFU - while picking up the Brexit referendum, displays a dramatic jump in 2020; and by the fact that GPR peaks in correspondence of the US invasion of Iraq in March 2003. Such measures point to a persistently high uncertainty at the end of the sample, while our measure (as typical of financial volatility measures) is characterized by a lower degree of persistence. All in all, we interpret the evidence in this Figure, which points to correlations between GFU and some extant measures of uncertainty ranging from zero to no more than 0.71, as supportive of the genuinely new information on global uncertainty carried by GFU.

Going back to our estimated factors, we document the correlations between GFU and our regional and country-specific factors in our Appendix for the sake of brevity, but offer a few brief comments here. GFU is highly correlated with regional factors such as the North American one, the European one, and the one associated to Oceania, as well as those of countries such as the US, the UK, Germany, and Australia. While these correlations are all similarly high (about 0.9), there might be different drivers behind them. The correlation between GFU and the North American factor is arguably driven by the role played by the US on the international financial markets, and by its strong influence on many countries around the world. The influence of first and second-moment shocks originating in the US economy on the Canadian economy (which belongs to the North American region) is obviously strong and well documented (see, e.g., Justiniano and Preston (2010) and Caggiano, Castelnuovo, and Figueres (2020)). UK and Germany are influential players on the European financial market, with spillovers on the global scenario. Differently, Oceania is the textbook example of open economy region buffeted by external shocks, something which also explains the correlation between GFU and Australia's financial uncertainty factor. Interestingly, not all regions/countries in our sample feature a financial uncertainty factor highly correlated with GFU. In fact, the estimated financial factors associated to Asia and Latin America, as well as China, Japan, and Singapore (to name a few), are characterized by a much lower degree of correlation. This is likely to be due to the role played by idiosyncratic events such as the tax reforms that generated uncertainty in China in the early 1990s, or the crisis triggered by the collapse of the Thai Baht in 1997, for the case of Asia, and the Peso and debt crisis in Argentina and Mexico. Going back to Europe, countries belonging to the Mediterranean area such as Italy and Greece feature financial volatility factors less synchronized with respect to the rest of Europe and the world as a whole, a fact possibly related to the exchange rate crisis that affected Italy in the early 1990s and the debt crisis in Greece in 2012. All our estimated regional factors, as well as a selection of country-specific ones, are documented in our Appendix.

5 VAR Analysis

Reduced-form VAR. We consider the three-variable system $\mathbf{X}_t = [GFU_t, GFC_t, 100\log(WIP_t)]'$, where GFU is our global financial uncertainty index, GFC is the global financial cycle estimated by Miranda-Agrippino and Rey (2020), and WIP stands for the level of world industrial production computed by Baumeister and Hamilton (2019).[15] The first two

[15] Small-scale VARs to investigate the drivers of the world business cycle have been employed by, among others, Kilian (2009), Kilian and Murphy (2012), Kilian and Murphy (2014), Antolín-Díaz and Rubio-Ramírez (2019), and Baumeister and Hamilton (2019). Omitted factors that are likely to influence world output such as oil shocks and US monetary policy shocks may spuriosly inflate the business cycle contribution of the GFU shocks identified in this paper. Our set of narrative restrictions

variables are modeled in levels, while WIP - as indicated above - is modeled in logs and multiplied by one hundred. The sample is July 1992 - April 2019, and its span is dictated by the availability of Miranda-Agrippino and Rey's (2019) global financial cycle estimate. Moreover, the omission of the observations related to the 2020 COVID-19 pandemic minimizes the risk of distortions of the VAR coefficients and, therefore, the VAR impulse responses due to such pandemic-related outliers (Lenza and Primiceri (2020)).[16]

The reduced-form finite-order VAR representation reads:

$$\mathbf{X}_t = \sum\nolimits_{j=1}^{p} \mathbf{A}_j \mathbf{X}_{t-j} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim (0, \boldsymbol{\Omega}) \tag{3}$$

where $\mathbf{A}_j$ are matrices of coefficients, $\boldsymbol{\eta}_t$ is the vector of error terms whose variance-covariance is $\boldsymbol{\Omega}$, and $\boldsymbol{\Omega} = \boldsymbol{P}\boldsymbol{P}'$, where $\boldsymbol{P}$ is the unique lower-triangular Cholesky factor with non-negative diagonal elements. The VAR features equation-specific constants and linear trends. We set $p = 3$, as suggested by the Schwarz information criterion.

Identification. We move from the reduced-form VAR (3) to the structural one as follows. First, we assume that the system of contemporaneous relationships mapping reduced form residuals $\boldsymbol{\eta}_t$ and structural shocks $\mathbf{e}_t$ can be described as

$$\boldsymbol{\eta}_t = \boldsymbol{B}\mathbf{e}_t, \quad \mathbf{e}_t \sim (0, \boldsymbol{I_n}) \tag{4}$$

where $\boldsymbol{B}$ is a matrix featuring n^2 elements. Given that the reduced form covariance matrix $\boldsymbol{\Omega}$ features only $n(n+1)/2$ elements, further restrictions have to be imposed to identify the effects of the structural shocks $\mathbf{e}_t$ on the endogenous variables $\mathbf{X}_t$. Without such further restrictions, infinitely many solutions would satisfy the covariance restrictions $\boldsymbol{\Omega} = \boldsymbol{B}\boldsymbol{B}'$. We collect a number $K = 500,000$ of these solutions into the set $\mathcal{B} = \{\boldsymbol{B} = \boldsymbol{P}\boldsymbol{Q} : \boldsymbol{Q} \in \mathcal{O}_n, diag(\boldsymbol{B}) \geqslant 0, \boldsymbol{\Omega} = \boldsymbol{B}\boldsymbol{B}'\}$, where $\mathcal{O}_n$ is a set of orthonormal matrices (i.e., $\boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{I_n}$). The set $\mathcal{B}$ is constructed by implementing the algorithm proposed by Rubio-Ramírez, Waggoner, and Zha (2010). We rotate $\boldsymbol{B}$ by drawing K random orthogonal matrices $\boldsymbol{Q}$. Each rotation is performed by drawing a matrix $\boldsymbol{M}$ from a multivariate normal $\mathcal{N}(\mathbf{0}, \boldsymbol{I_n})$ density. Then, $\boldsymbol{Q}$ is taken to be the orthonormal

(described later in the paper) features restrictions designed to control for these two factors.

[16] Obviously, one could note that such observations have been included in the sample we work with when estimating our global financial factor. Our Appendix contrasts the estimate of the GFU factor obtained by including vs. omitting COVID-19-related observations. It turns out that the dynamic hierarchical factor model we employ basically returns the same estimate of the GFU factor in the pre-COVID-19 sample. For a recent paper computing financial (and macroeconomic) uncertainty for the US with a factor approach that models the extreme volatility of the COVID-19 observations, see Carriero, Clark, Marcellino, and Mertens (2020).

matrix in the $\boldsymbol{QR}$ decomposition of $\boldsymbol{M}$. Given that $\boldsymbol{B} = \boldsymbol{PQ}$ and $\boldsymbol{QQ}' = \boldsymbol{I_n}$, the covariance restrictions $\boldsymbol{\Omega} = \boldsymbol{BB}'$ are satisfied. Let $\mathbf{e}_t(\boldsymbol{B}) = \boldsymbol{B}^{-1}\boldsymbol{\eta}_t$ be the shocks implied by $\boldsymbol{B} \in \mathcal{B}$ for a given $\boldsymbol{\eta}_t$. Then, K different $\boldsymbol{B}$ imply K unconstrained $\mathbf{e}_t(\boldsymbol{B}) = \boldsymbol{B}^{-1}\boldsymbol{\eta}_t$, $t = 1, ..., T$.

While the set $\mathcal{B}$ contains infinitely many (in our case, K) solutions mathematically coherent with equations (3)-(4), not all these solutions are equally interesting from an economic standpoint. We identify the set of admissible solutions $\overline{\mathcal{B}}$ that can be considered as economically sensible conditional on our research question by imposing different types of identification restrictions, i.e., event constraints, external variable constraints, and sign restrictions.

Event constraints. Event constraints are constraints imposed directly on the shocks $\mathbf{e}_t(\boldsymbol{B})$ (Antolín-Díaz and Rubio-Ramírez (2019), Ludvigson, Ma, and Ng (2019a,b)). We impose constraints on dates that are associated to large jumps in financial uncertainty which have a clear interpretation from an historical standpoint. The idea is that such large jumps may be mostly exogenous and, therefore, associated to GFU shocks. To identify the dates of interest, we proceed as follows. First, we compute the median values over time of the GFU shocks corresponding to all admissible models. Second, we search for the largest realizations of such median. In particular, we focus on those that take a value larger than two standard deviations of the time series of the median values itself. As shown in Figure 5, we isolate six historical events that have substantially increased the volatility of financial markets worldwide: the Russian crisis and LTCM default in August 1998, 9/11, the Worldcom and Enron scandals in June 2002, the acceleration of the Great Recession due to Lehman Brothers' bankruptcy in September 2009, the Greek crisis in April 2010, and the Eurozone crisis in August 2011. We then assume that GFU shocks should take "large" realizations in correspondence of these events. In particular, we require GFU shocks realizations in these dates to be larger than the median of the distribution of the shocks generated by all retained models in these dates, with the exception of the Great Recession case, where our requirement is that GFU shocks realizations have to be larger than the 75th percentile of such distribution.

Following Ludvigson, Ma, and Ng (2019b), we also require "output shocks" to be consistent with the idea of a global downturn during the Great Recession of December 2007 - June 2009, which is the dating of the US recession by the NBER. Technically, we impose that the sum of the realizations of the output shocks in that period be negative. This is done in an attempt of separating GFU shocks from other shocks in our VAR, something which should work in favor of selecting out models that are not economically plausible (the models meeting our event constraints but at the same time implying expansionary output shocks during the Great Recession).

Correlation constraints. Our parsimonious three-variable VAR does not model shocks that have recently been shown to be drivers of GFC and WIP. In particular, Miranda-Agrippino and Rey (2020) find US monetary policy shocks to be followed by significant movements in their global financial cycle, while Baumeister and Hamilton (2019) identify oil supply shocks as the most important driver of their measure of world industrial production. As stressed by Canova and Ferroni (2019), the risk one runs when omitting relevant shocks is to identify convolutions of primitive shocks instead of isolating the shocks of interest. To minimize this risk, we require our models to return a correlation between GFU shocks and Miranda-Agrippino and Rey's (2019) US monetary policy shocks on the one hand, and GFU shocks and Baumeister and Hamilton's (2019) shocks on the other, to be lower than 0.05.[17]

Impulse response constraints. We further sharpen the identification of our GFU shocks by imposing two different types of sign restrictions on the impulse responses $IRF(\boldsymbol{B}, \mathbf{A}j)$. First, we require a positive global financial (output) shock to be expansionary (generate a positive response of the global financial cycle) on impact. The idea here is to sharpen the identification of global financial and output shocks and, therefore, separate these shocks more convincingly from the GFU shocks we are after. Other restrictions are imposed to overcome the identification issue one faces when attempting to separate first and second moment financial shocks, a notoriously challenging task (for a discussion, see Stock and Watson (2012); for evidence on the correlation between the VIX and the global financial cycle, see Rey (2018)). Following Furlanetto, Ravazzolo, and Sarferaz (2019), we work further to separate first moment (GFC) and second moment (GFU) financial shocks by imposing that a GFU (GFC) shock implies a on-impact positive (negative) response of the GFU/GFC ratio.[18]

[17] We do not require our and their estimates of the shocks to be exactly orthogonal for two reasons. First, our analysis is necessarily a (limited) sample analysis (as opposed to a population analysis). Second, US monetary policy and oil supply shocks are estimated objects, therefore surrounded by statistical uncertainty. An alternative to this way of implementing the correlation restrictions is to discard all models with estimated correlations that are not significantly different from zero at a given significance level. Our results are robust to working with this alternative restrictions (significance level: 5%).

[18] To impose meaningful sign restrictions on the responses of the GFU/GFC ratio, we adjust the GFC series so that its first two moments are equivalent to those of the GFU series. Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) separate first and second moment shocks by appealing to a penalty function identification strategy which relies on the ordering of the two first and second moment proxies

The set of constraints imposed in our analysis is collected in Table 2. The joint imposition of the above described constraints on the set of unconstrained models $\mathcal{B}$ delivers a set of 406 (0.08% of K) admissible solutions $\overline{\mathcal{B}}$, which we employ to study the macroeconomic effects of GFU shocks. Table 2 also reports the impact of each different type of restriction on the unconstrained set B . All sets of different restrictions, assessed one-by-one, narrow such a set. When imposing only the event based restrictions related to the historical events characterized by high realizations of the GFU shocks, we end up retaining just 11.21% of the 500,000 models of our unconstrained set. The restrictions requiring an expansionary effect of global financial shocks, as well as improvement of financial conditions after a positive "output" shock, eliminate about 4/5 of the models in the B set. The restrictions imposed to separate first and second-moment financial shocks also turn out to be powerful, with just about 33% of the models retained after their imposition. The requirement of output "shocks" mostly being negative during the most acute phase of the Great Recession discards about 31% of the models. Finally, the most selective restrictions are the correlation constraints, which discard about 93% of the models in the unconstrained set B. We interpret this evidence as a validation of the use of these restriction sets.

5.1 IRFs and FEVD

Figure 6 plots the impulse response functions of global financial uncertainty, the global financial cycle, and world industrial production to a one standard deviation GFU shock. Following Baumeister and Hamilton (2020), we plot the impulse responses implied by all our retained draws to have a complete picture of the implications of our identifying restrictions. A few facts emerge. First, the response of GFU to its own shock peaks around two months after the shock, then goes gradually back to zero within one year. Second, the response of GFC is hump shaped (as the GFU and WIP ones), but takes longer to go back to zero (about two years). Third, the response of World IP peaks around ten months-to-one year after the shock, and goes back to zero after 2-1/2 years. Notably, the peak response of GFC and WIP is clearly negative for all retained models. Model uncertainty implies different point estimates of the peak response of world industrial production to a GFU shock. Panel [2,2] in Figure 6 plots the histogram of such peak response, which is constructed by collecting the maximum negative value of the impulse response of each model. The median realization of this distribution is -0.27,

in the vector. The advantage of the identification restriction pursued here is that it does not require to assume a recursive economy.

i.e., world industrial production falls by 0.27% in response to an one standard deviation jump in global financial uncertainty, while the set of retained models points to a drop in world output ranging from 0.61% down to 0.09%.

Table 3 collects the figures regarding the forecast error variance decomposition at business cycle frequencies, which are here proxied by 2 and 4-year forecast horizons. The contribution of GFU shocks to the world business cycle is around 9%, just slightly lower than that by global financial cycle shocks. The global financial cycle is found to be importantly driven by both GFU shocks (about 30%) and business cycle shocks (about 45%). GFU is mostly affected by its own shock, but does also respond to world output shocks (about 22-27%, depending on the horizon one considers) and global financial shocks (10%).

5.2 GFU shocks and the Great Recession

The world output effects due to GFU shocks documented in Section 5.1 are computed conditional on a one-standard deviation GFU shock. However, as shown in Figure 5, according to our model the Great Recession was characterized by a much larger jump in GFU. We then compute the contribution of GFU shocks during the Great Recession - conditional on each one of our retained models - as follows. First, we use our VAR to simulate the evolution of our endogenous variables (GFU, GFC, WIP) in a counterfactual scenario in which GFU shocks are set to zero during the Great Recession and its aftermath, period 2008M9-2012M12. The choice of this period, which is meant to capture the global downturn during the Great Recession, is justified by the recent analysis on global business cycles put forth by Kose and Ohnsorge (2019), who identify 2009 as the year of the Great Recession, and also point out the fact that 2012 was a year in which the global economic downturn occurred. Then, we quantify the "World Industrial Production Great Recession loss" by computing the distance between the counterfactual world industrial production that (according to our VAR) we would have observed in absence of GFU shocks and the actual one, and re-expressing this distance in yearly terms. Formally, we compute:

$$\mathcal{L}_{WIP|e_{GFU.GR}} = \frac{1200}{52} \sum\nolimits_{t=2008M9}^{2012M12} \log\left(\frac{WIP_t|\, e_{GFU.t} = 0}{WIP_t}\right) \tag{5}$$

The factor $\frac{1200}{52}$ in (5) rescales the cumulative loss during and after the Great Recession by the number of months in the 2008M9-2012M12 period (52), then multiplies it by 1200 to make the loss interpretable as annualized percent deviation of the world industrial production index in absence of GFU shocks with respect to the actual WIP.

Figure 7 (left panels) plots the evolution of the simulated path that WIP would have followed if no GFU shocks had materialized (and contrasts it with the actual WIP series) according to two of our retained models, i.e., the one that implies the minimum output loss during the period under analysis and the one that implies the maximum loss. The two different scenarios implied by these two different structural models offer strikingly contrasting indications. In one case (that of the minimum loss), the contribution of the GFU shocks appears to be small, if not negligible. The opposite conclusion can be drawn when looking at the maximum loss case, GFU shocks emerge as relevant drivers of the severe drop and slow recovery of the world economy experienced in the period under scrutiny. The distribution of the $\mathcal{L}_{WIP|e_{GFU.GR}}$ statistic (5), constructed by plotting the histogram of the values of such statistic conditional on all retained models $\overline{\mathcal{B}}$ and shown in the right panel of Figure 7, point to a loss ranging from 3% to 27%, with a median value of 13%.

5.3 Finance uncertainty multiplier

What does our model suggest as for the financial costs due to GFU shocks during the Great Recession? Figure 8 juxtaposes the counterfactual simulations on the paths of WIP in absence of GFU shocks already proposed in Figure 8 with the corresponding simulations of the counterfactual paths the global financial cycle would have followed in absence of GFU shocks. It is important to stress that the counterfactual simulations of both WIP and GFC in the upper (lower) panels correspond to the model which implies the lowest (highest) world industrial production loss according to our set of retained rotations $\overline{\mathcal{B}}$. A correlation seems to arise. When the output cost due to GFU shocks is small, the impact of GFU shocks on the global financial cycle is also small. Instead, when the loss in world industrial production is large, the financial cycle is also found to be substantially deteriorated.

Is the correlation between world industrial production and global financial cycle losses robust across our retained models $\overline{\mathcal{B}}$? To address this question, we first compute, per each retained model, the global financial cycle loss occurred during the Great Recession and due to GFU shocks. We quantify such loss as follows:

$$\mathcal{L}_{GFC|e_{GFU.GR}} = \frac{12}{52} \sum\nolimits_{t=2008M9}^{2012M12} (GFC_t|\, e_{GFU.t} = 0 - GFC_t) \qquad (6)$$

We then scatter-plot the values of the losses (5) and (6) across the set of retained models $\overline{\mathcal{B}}$ to see if there is any correlation between these two objects. Figure 9 captures such correlation. Most of the models identify an impressively precise positive correlation between these two losses, with just a few models deviating from it. Quite interestingly, this correlation is consistent with the existence of a causal link between uncertainty, financial frictions, and real activity as the one formalized in the frameworks proposed by Gilchrist, Sim, and Zakrajšek (2014), Arellano, Bai, and Kehoe (2019), and Alfaro, Bloom, and Lin (2019). The latter paper term "finance uncertainty multiplier" the toxic interaction between uncertainty shocks and financial frictions that sees the latter magnify the real effects of the former.

Before concluding, it is important to stress that the results of set-identification exercises as the one conducted in this paper may be affected by the seed that initializes the stochastic simulations one conducts when searching for models meeting the identifying constraints. Moreover, the Haar distribution on rotation matrices Q can actually imply non-uniform distributions over objects such as impulse responses, or the finance-uncertainty multiplier. Both points are made in Baumeister and Hamilton (2020). Our Appendix documents the robustness of our results to the use of different seeds, as well as the impact of our identifying restrictions on the impulse responses and the finance uncertainty multiplier documented in this paper.

6 Conclusions

About a decade after the Great Recession, the recent COVID-19 outbreak has reminded us the importance of understanding the macroeconomic effects of uncertainty shocks at a global level. We tackle this challenge by proceeding in two steps. First, we propose a new measure of global financial uncertainty. Our measure, which we term GFU, is extracted from a large cross-country dataset of monthly volatility data, which are modeled using a multi-level factor framework so that we can jointly estimate regional and country-specific uncertainty measures. Unlike measures of global political uncertainty, global financial uncertainty does not display any time trend. It peaks in correspondence of well identified historical events, such as, among others, the Asian and Russian crises of the late 1990s, the 9/11 2001 terrorist attack, the second Gulf War, the Great Recession, the European sovereign debt crisis, Brexit, and the materialization in March 2020 of the COVID-19 pandemic. Second, we estimate a structural VAR model with our GFU index along with global measures of financial stress and industrial production. Using an identification approach based on different types of restrictions, we identify global financial uncertainty shocks, and disentangle them from first moment global financial shocks. Our VAR estimates the loss in world output that can be attributed to the spike in global uncertainty during the Great Recession in about 13% yearly (median estimate), and suggests that such a loss might have been as large as 27%. The evidence coming from our VAR points to the possibility of a global finance uncertainty multiplier, i.e., financial stress following an increase in uncertainty might have contributed to the deterioration of global output.

Our findings support the macro-finance literature that has highlighted the importance of modeling jointly first and second moment financial shocks, e.g. Gilchrist, Sim, and Zakrajšek (2014), Arellano, Bai, and Kehoe (2019), and Alfaro, Bloom, and Lin (2019). Global shocks that increase uncertainty are likely to trigger a sizeable contraction in real activity especially if they can cause financial disruptions. Our findings support swift policy interventions aimed at maintaining the credit market in check to limit at much as possible the real effects of uncertainty shocks. This is exactly what central banks and Governments have done in response to the COVID-19 pandemic. Our results suggest that such policy moves might have prevented a fall in global output even larger than the one we have observed.

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North America	**Europe**	**South America**
Canada	Austria	Argentina
Mexico	Belgium	Brazil
United States	Czech Republic	Chile
	Denmark	Colombia
	Finland	Peru
	France	
Asia	Germany	**Oceania**
China	Great Britain	Australia
Hong Kong	Greece	New Zealand
India	Hungary	
Indonesia	Ireland	
Japan	Italy	
Korea	Netherlands	
Malaysia	Norway	
Pakistan	Poland	
Philippines	Russia	
Singapore	Spain	
Taiwan	Sweden	
Thailand	Switzerland	
	Turkey	

Table 1: **Countries and regions covered by our dataset.**

t	Event	Restriction	% retained draws
	Event restrictions		
1998M8	Russian, LTCM default	$e_{GFU.t} > P_{50}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	
2001M9	9/11	$e_{GFU.t} > P_{50}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	
2002M6	Worldcom, Enron	$e_{GFU.t} > P_{50}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	11.21%
2008M9	Great recession	$e_{GFU.t} > P_{75}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	
2010M4	Greek crisis	$e_{GFU.t} > P_{50}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	
2011M8	Eurozone crisis	$e_{GFU.t} > P_{50}(\mathbf{e}_{GFUt}(\boldsymbol{B}))$	
2007M10-2009M6	Great recession	$0 > \sum_{t=2007M12}^{2009M6} e_{WIP.t}$	69.07%
	Correlation restrictions		
	$\lvert\rho(e_{GFU.t}, e_{USMPt})\rvert < 0.05$	$\lvert\rho(e_{GFU.t}, e_{OILt})\rvert < 0.05$	6.94%
	Sign restrictions		
	$\frac{\partial WIP_t}{\partial e_{GFC.t}} > 0$	$\frac{\partial GFC_t}{\partial e_{WIP.t}} > 0$	19.49%
	Ratio restrictions		
	$\left\lvert\frac{\partial GFU_t}{\partial e_{GFC.t}}\right\rvert < \left\lvert\frac{\partial GFC}{\partial e_{GFC.t}}\right\rvert$	$\left\lvert\frac{\partial GFU_t}{\partial e_{GFU.t}}\right\rvert > \left\lvert\frac{\partial GFC}{\partial e_{GFU.t}}\right\rvert$	32.86%
	Entire set of restrictions		0.08%

Table 2: **Set of identifying restrictions.** Constraints imposed to identify global financial uncertainty and separate them from global financial cycle shocks and global output shocks. GFU stands for global financial uncertainty; GFC for global financial cycle; WUI for World Industrial Production. The last column reports the percentage of draws meeting each subset of restrictions, as well as (last row) the entire set of constraints we impose to identify the GFU shocks.

Variable/shock	e_{GFU}	e_{GFC}	e_{WIP}
	2-year horizon		
GFU	69.12% [53.23%,82.88%,]	9.02% [7.46%,11.04%,]	21.62% [9.41%,36.99%,]
GFC	30.73% [16.61%,63.45%,]	22.97% [15.60%,33.29%,]	44.85% [13.48%,66.30%,]
WIP	8.91% [1.92%,44.29%,]	10.11% [5.27%,18.56%,]	79.74% [47.75%,92.56%,]
	4-year horizon		
GFU	63.35% [47.82%,79.44%,]	9.66% [8.05%,11.98%,]	26.94% [12.51%,42.43%,]
GFC	30.74% [16.59%,63.51%,]	22.90% [15.54%,33.20%,]	44.93% [13.51%,66.38%,]
WIP	9.34% [1.98%,45.15%,]	10.11% [5.24%,18.53%,]	79.37% [46.86%,92.51%,]

Table 3: **Forecast Error Variance Decomposition.** Forecast error variance decomposition conditional on our retained models. Figures refer to the median value across retained models of the contribution of each given shock for each given variable at selected horizons. Figures in brackes: Minimum and maximum contributions according to our selected models. The sum of the contributions of the shocks per each given variable does not return 100 percent because this Table considers moments of distributions across the different models of our retained set.

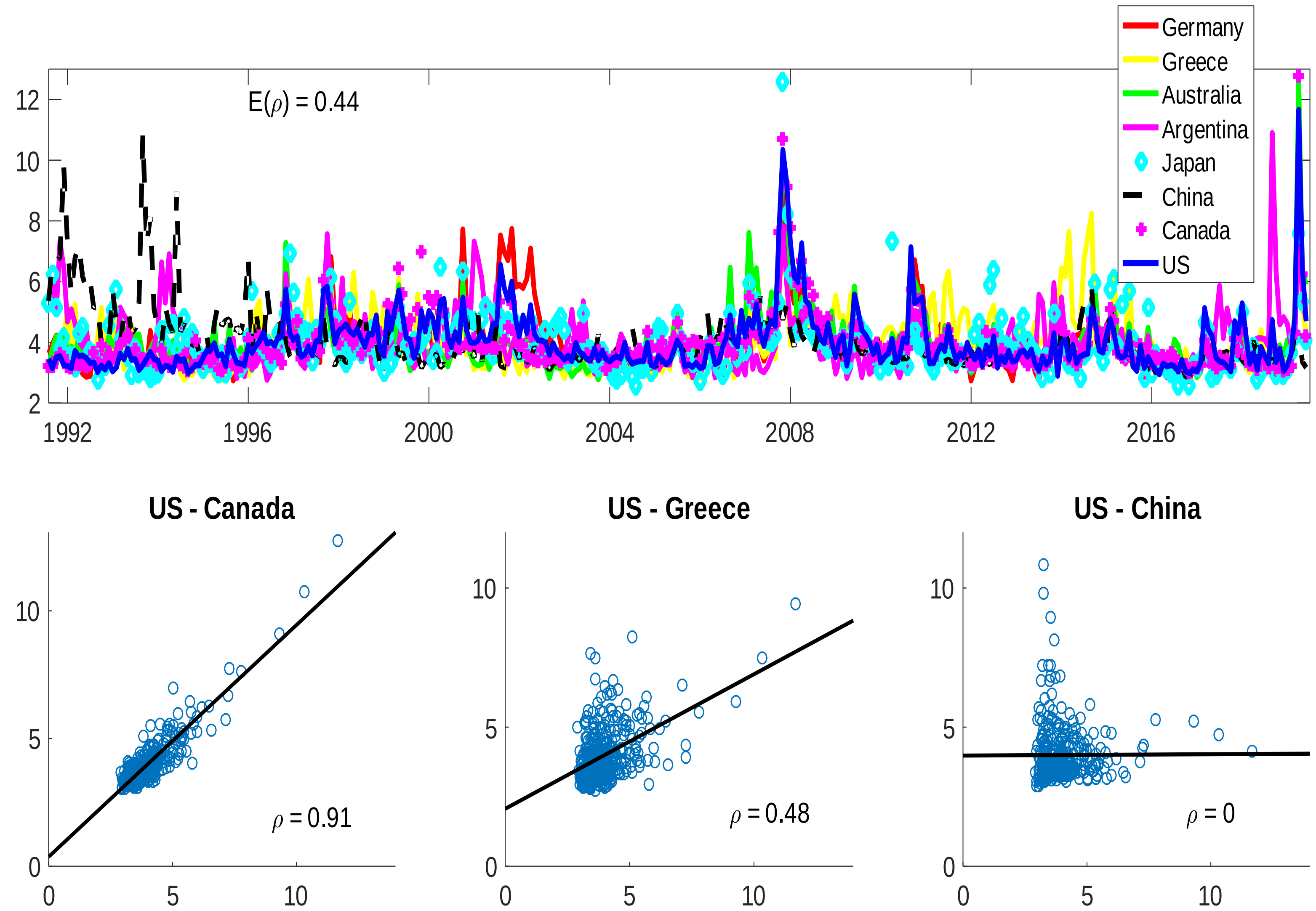

Figure 1: **Financial volatilities around the world.** Upper panel: Stock market returns volatility, selected countries. Lower panels: Scatter plots of stock market returns volatilities, selected pairs of countries. .

Figure 2: **Caggiano and Castelnuovo's (2019) Global Financial Uncertainty Measure.** GFU factor estimated with a dynamic hierarchical factor model à la Moench et al. (2013) combined with the algorithm designed to take care of missing observations in unbalanced panel by Banbura and Modugno (2014). GFU is the global-level factor of the DHFM that jointly models regional, country-specific, and series-specific factors.

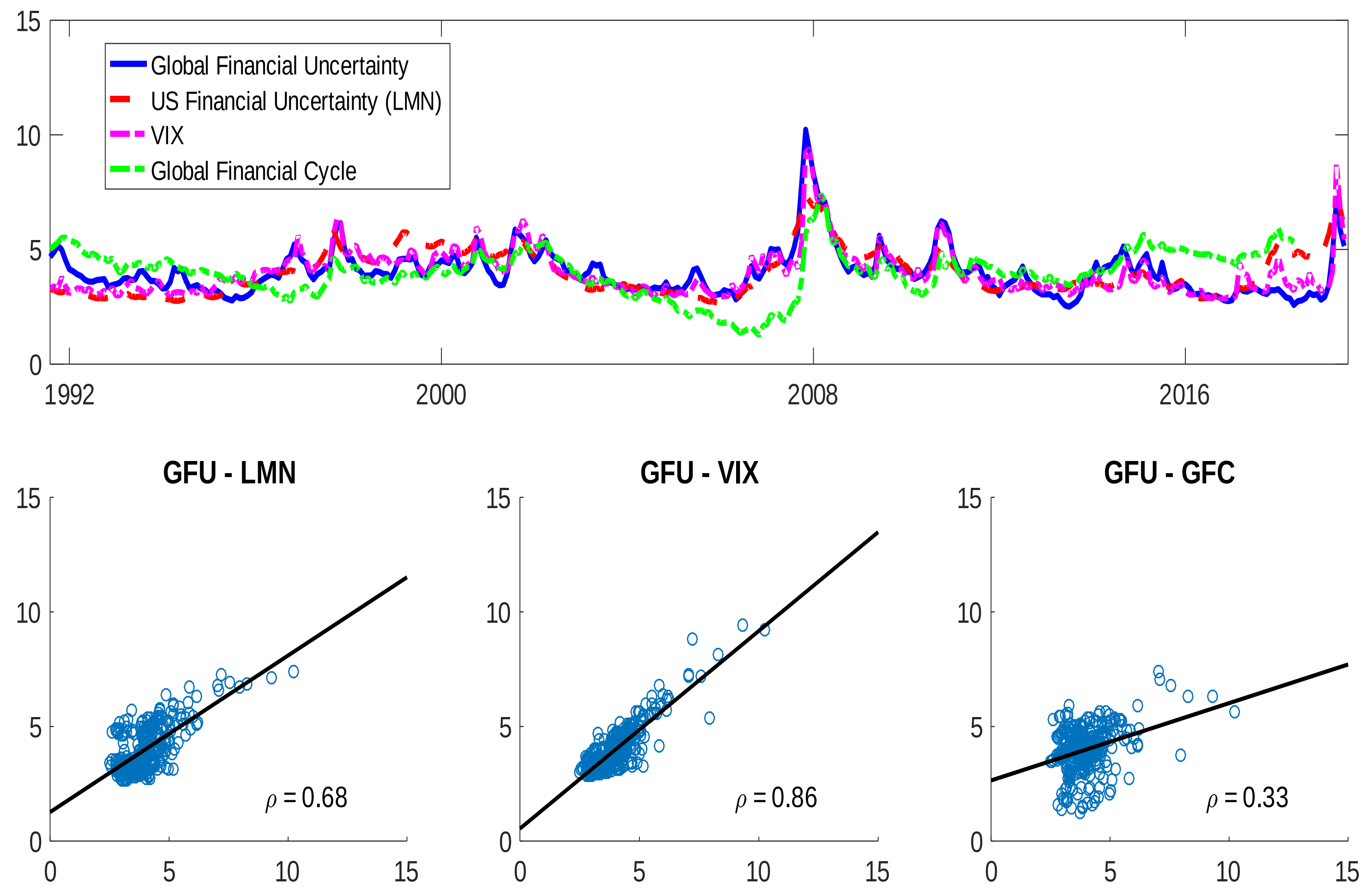

Figure 3: **Global Financial Uncertainty vs. Alternative Financial and Uncertainty Measures.** Upper panel: Global Financial Uncertainty as in Caggiano and Castelnuovo (2019) vs. Ludvigson et al.'s (2019) US financial uncertainty index, Miranda-Agrippino and Rey's (2020) global financial cycle index, and the VIX. Lower panel: Pairwise correlations. All series in this Figure are normalized to have the same mean and standard deviation of the GFU series. Global Financial Cycle's sign (upper panel) flipped to ease comparability.

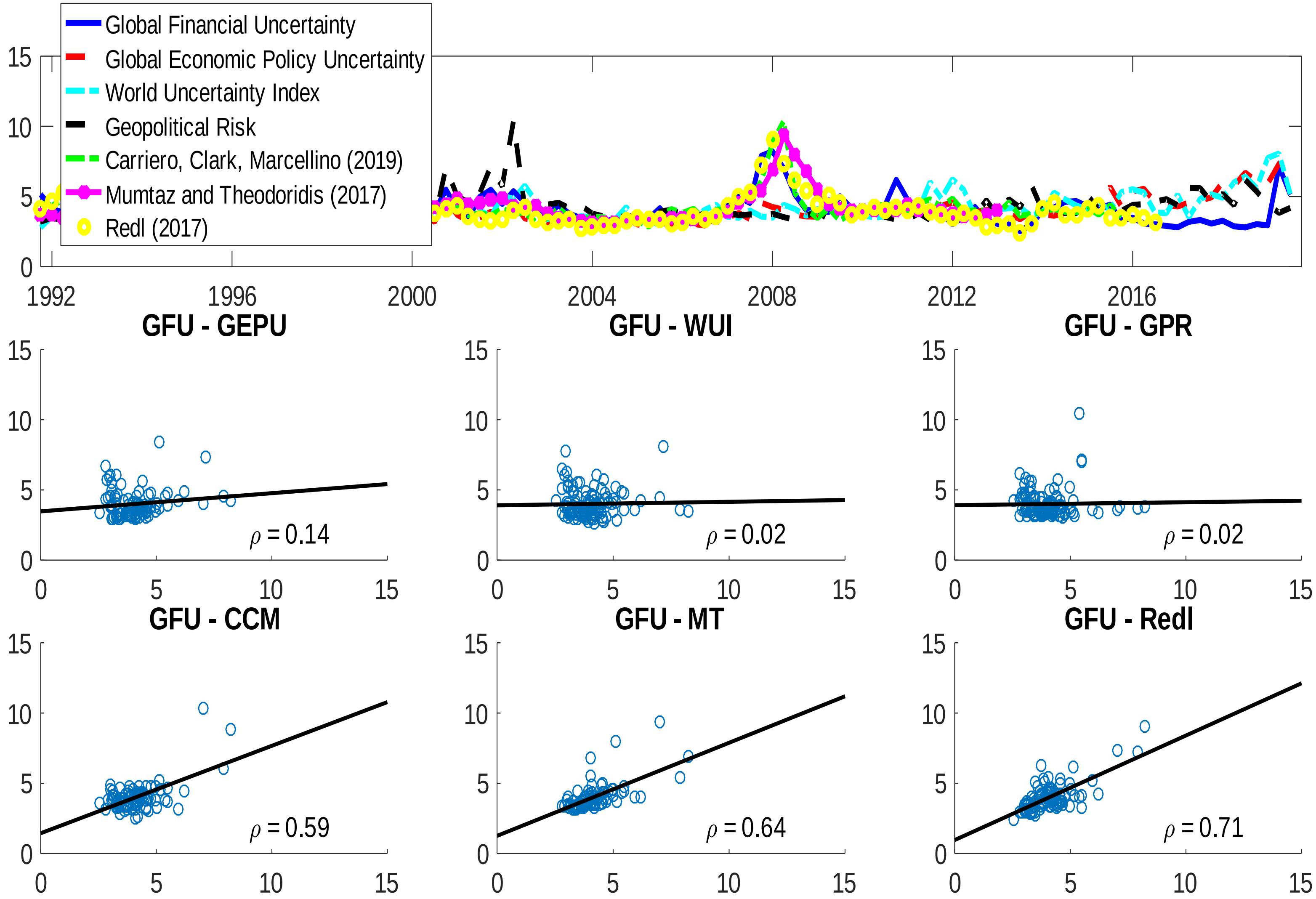

Figure 4: **Global Financial Uncertainty vs. Alternative Global Uncertainty Measures.** Upper panel: Global Financial Uncertainty as in Caggiano and Castelnuovo (2020) vs. Global Economic Policy Uncertainty as in Davis (2016), Geopolitical Risk as in Caldara and Iacoviello (2019), World Uncertainty Index as in Ahir, Bloom, and Furceri (2018), and Global Macroeconomic Uncertainty as in Carriero, Clark, and Marcellino (2019), Mumtaz and Theodoridis (2017) and Redl (2017). Quarterly frequencies. All series in this Figure are normalized to have the same mean and standard deviation of the GFU series.

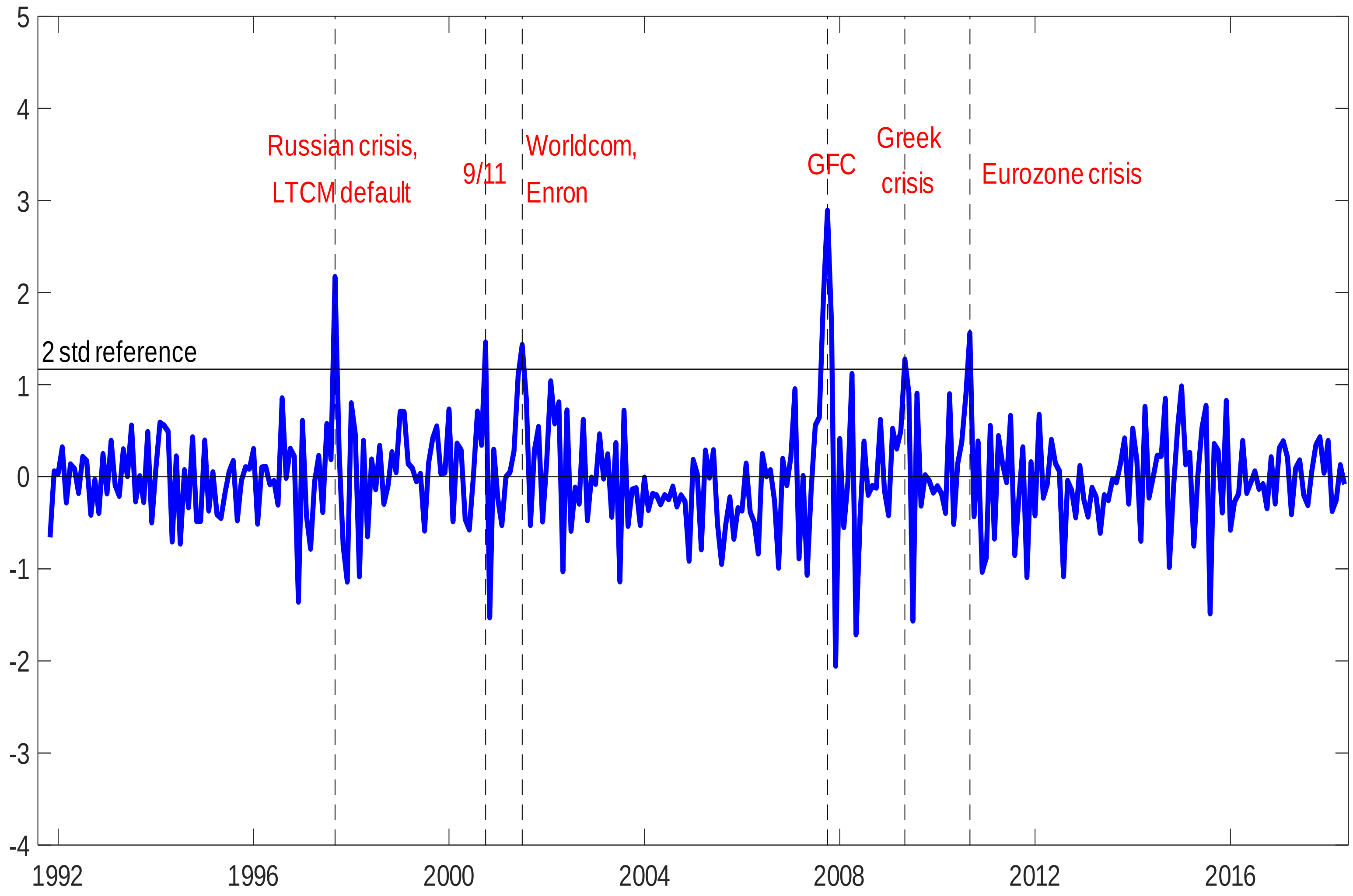

Figure 5: **Unconstrained shocks: Median across realizations.** Dates identified with dashed vertical lines are those corresponding to median values exceeding two standard deviations of the time series of the median realizations itself.

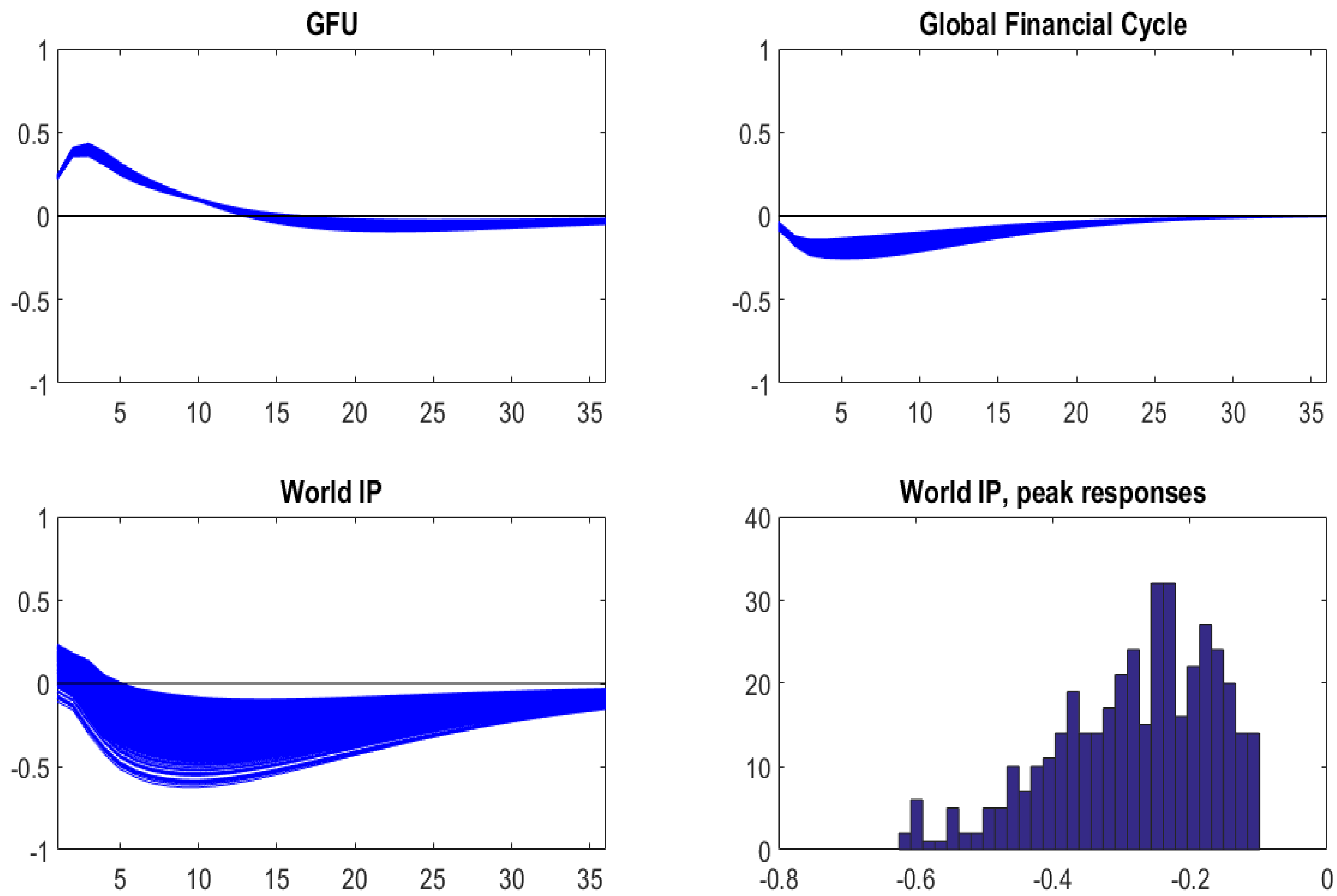

Figure 6: **Impulse Responses to a Global Financial Uncertainty Shock.** Sample: 1992M7-2019M4. Responses to an one standard deviation shock. Identification of the GFU shock achieved by imposing the restrictions reported in Table 2.

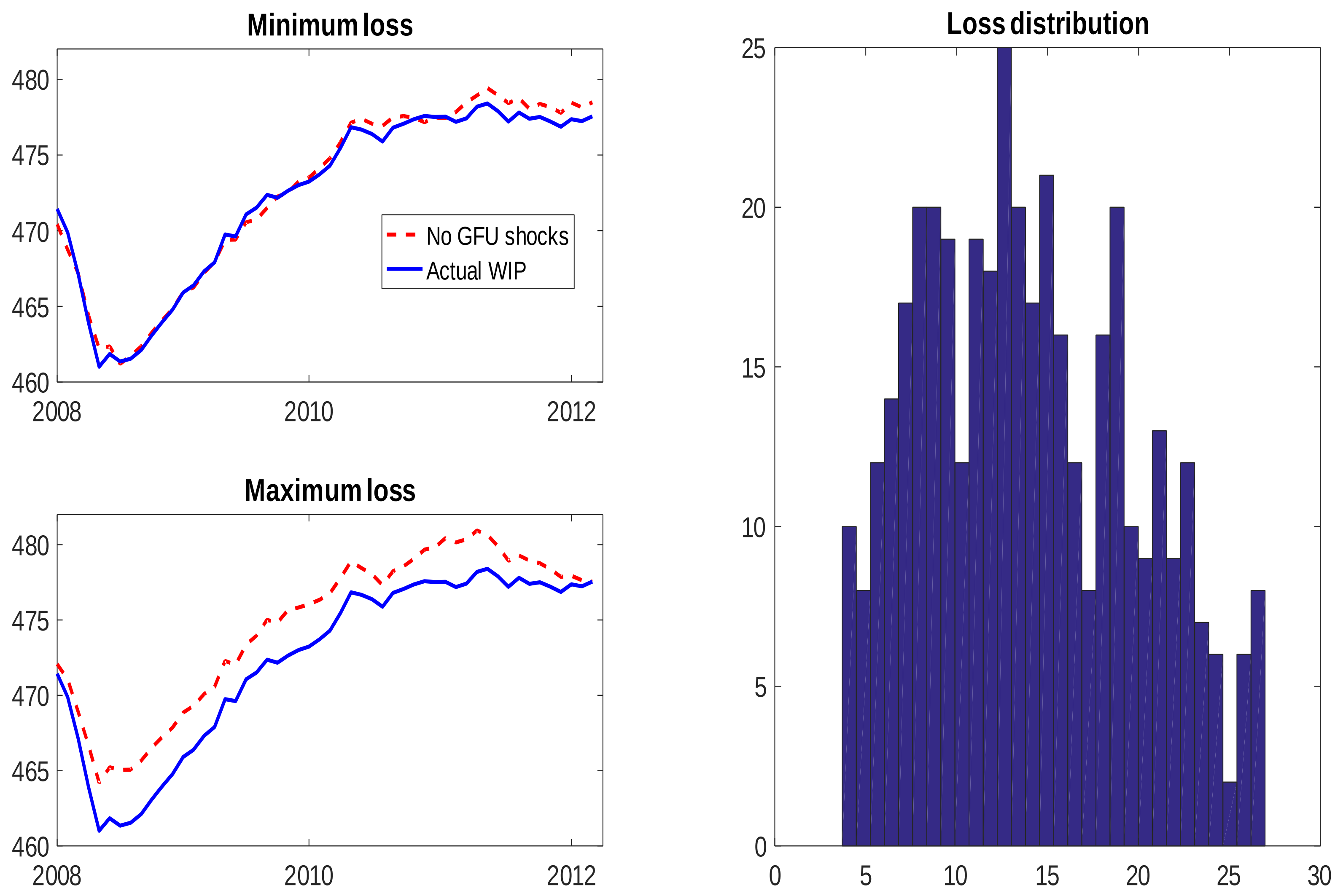

Figure 7: **Role of GFU shocks during the Great Recession: World Industrial Production, Counterfactual simulations.** Sample: 2008M9-2012M12. Left panes: Blue solid lines: Actual series. Red dashed-lines: Counterfactual series simulated with our estimated structural VAR by shutting down GFU shocks. Models associated with the minimum (upper left panel) and maximum (lower left panel) WIP loss plotted in the figure. Right panel: Distribution of the WIP loss across all retained models.

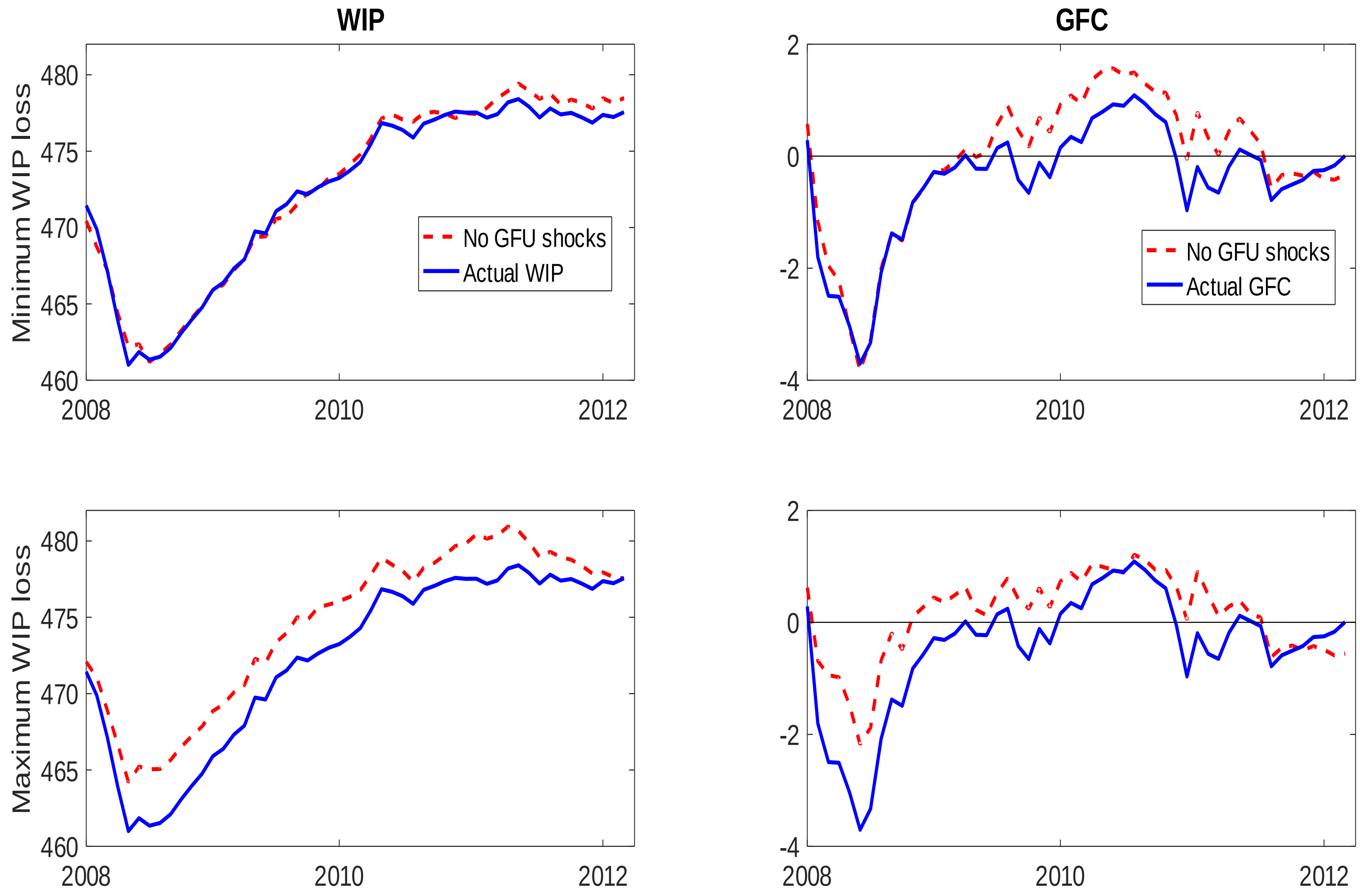

Figure 8: **Role of GFU shocks during the Great Recession: World Industrial Production and Global Financial Cycle, Counterfactual simulations.** Sample: 2008M9-2012M12. Left panes: Blue solid lines: Actual series. Red dashed-lines: Counterfactual series simulated with our estimated structural VAR by shutting down GFU shocks. Models associated with the minimum (upper left panel) and maximum (lower left panel) WIP loss plotted in the figure.

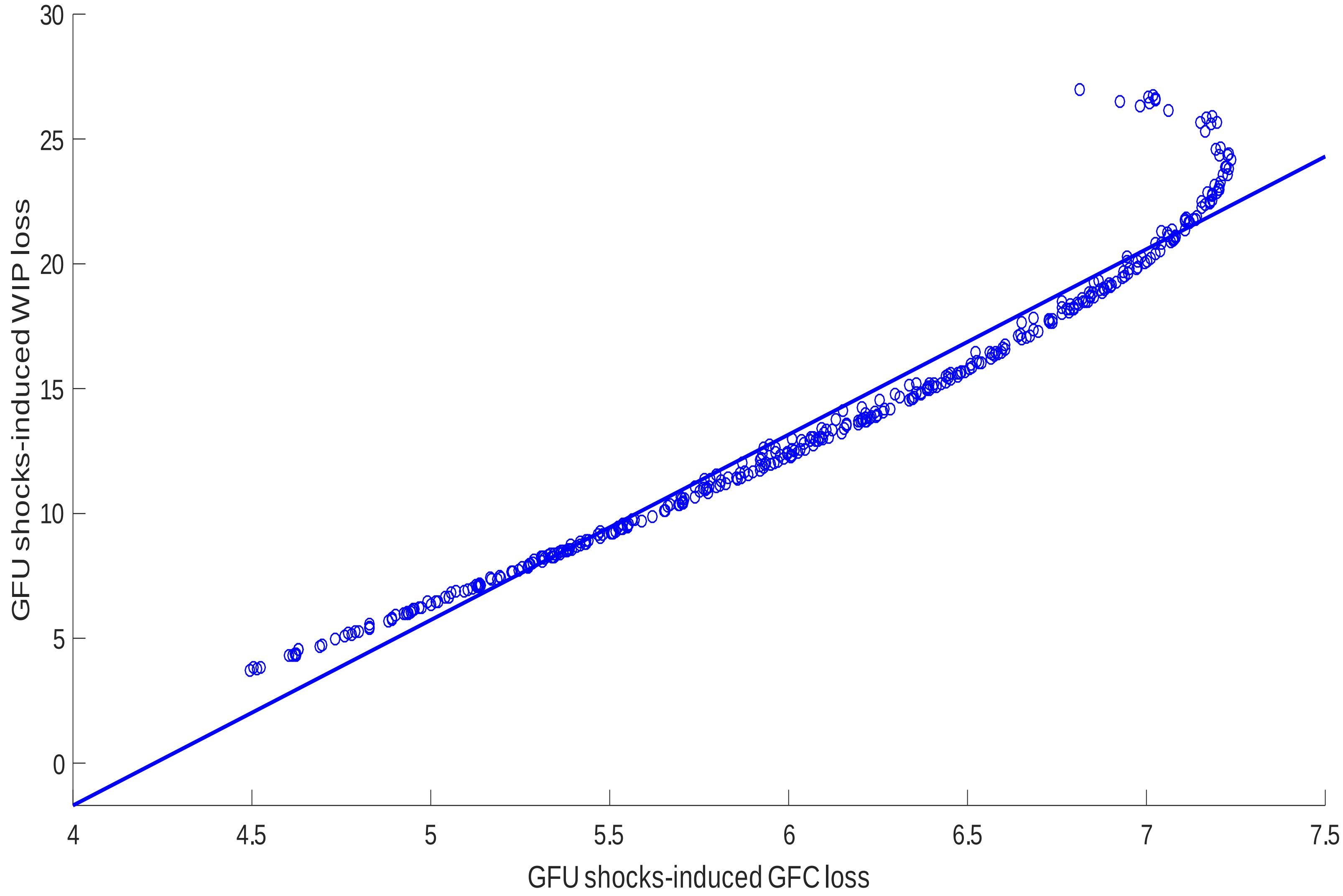

Figure 9: **Global Finance Uncertainty Multiplier.** Sample: 2008M9-2012M12. Scatter plot correlating the World Industrial Production loss and the deterioration of the Global Financial Cycle due to GFU shocks according to all our retained models.

Appendix of "Global Uncertainty" (Caggiano and Castelnuovo 2021)

This Appendix collects further information with respect to the one in our "Global Uncertainty" paper. In particular:

- Section A depicts the countries covered by our dataset.
- Section B shows that the Dynamic Hierarchical Factor Model (DHFM) we work with to estimate the Global Uncertainty Factor (GFU) can be interpreted as a time-varying intercept-model.
- Section C offers details on our algorithm to estimate the DHFM framework with an unbalanced panel.
- Section D supports the modeling of regional and country-specific blocks by contrasting our estimated global factor with the one estimated by principal components.
- Section E comments on our regional and country-specific factors.
- Section F plots the data used in our VAR analysis and the VAR impulse responses.
- Section G contrasts our estimate of the GFU obtained with the whole sample of available data (1992M7-2020M5) with the estimate we obtained by dropping the COVID-19 observations and ending the sample in 2020M2.
- Section H analyzes the role of different seeds for our stochastic simulations (in first place, for the algorithm we use to draw orthonormal rotation matrices to explore the set of admissible models conditional on the restriction we impose to identify macroeconomic shocks in our VAR analysis).
- Section I investigates the role played by the rotation matrices *per se* in influencing our results.

A: Our dataset: Geographical coverage

Figure A1 depicts the geographical coverage of our dataset, which features data of 42 countries and five continents.

B: Coefficients restrictions and time-varying intercepts in the DHFM

Consider the four level factor model of Section 3.2:

$$\begin{aligned} Z_{rcnt} &= \lambda^n_{C,rc}(L)\, C_{rct} + e_{Z_{rcnt}} \\ C_{rct} &= \Lambda_{R.rc}(L)\, R_{rt} + e_{C_{rct}} \\ R_{rt} &= \Lambda_{GFU.r}(L)\, GFU_t + e_{R_{rt}} \\ \Psi_{GFU}(L)\, GFU_t &= e_{GFU_t} \end{aligned} \tag{1}$$

where GFU_t is the common factor, $\Lambda_{GFU.r}(L)$ is the distributed lag of loadings on the common factor, $e_{R_{rt}}$ is the region-specific variation, R_{rt} is the $(k_R \times 1)$ vector of region-specific factors, where k_R denotes the number of regions, $\Lambda_{R.rc}(L)$ is the distributed lag of loadings on the region-specific factors, $e_{C_{rct}}$ is the country-specific variation, C_{rct} is the $(K_{Cr} \times 1)$ vector of country-specific factors, where K_{Cr} denotes the number of countries in region r, $\lambda^n_{C,rc}(L)$ is the distributed lag of loadings on the country-specific factors, and $e_{Z_{rcnt}}$ is the series specific variation. The idiosyncratic components, and the country specific, region specific, and global factors are assumed to be stationary, normally distributed autoregressive processes of order 1.

As the factors and the loadings are not separately identified, to achieve identification we follow Moench, Ng and Potter (2013) and assume i) that $\Lambda_\bullet(L) = \Lambda_\bullet$ is a constant lower triangular matrix of order 0, with elements having fixed signs on the diagonal, and ii) that the factors have fixed variances. The former normalization ensures that the sign of the factors is identified. This latter assumption is justified by the fact that the data are standardized to have unit variance.

The fact that the DHFM model (1) features time-varying intercepts can be made explicit by rewriting it as:

$$\begin{aligned} Z_{rcnt} &= \alpha_{CR,rcnt} + \Pi^n_{CR,rc}(L)\, GFU_t + e_{Z_{rcnt}} \\ \alpha_{CR,rcnt} &\equiv \Xi^n_{CR,rc}(L)\, e_{R_{rt}} + \lambda^n_{C,rc}(L)\, e_{C_{rct}} \\ \Pi^n_{CR,rc} &\equiv \lambda^n_{C,rc}(L)\, \Lambda_{R.rc}(L)\, \Lambda_{GFU.r}(L) \\ \Xi^n_{CR,rc}(L) &\equiv \lambda^n_{C,rc}(L)\, \Lambda_{R.rc}(L) \end{aligned} \tag{2}$$

where $\alpha_{CR,rcnt}$ are time-varying intercepts and $\Pi^n_{CR,rc}$ is a matrix of coefficient restrictions. This way of writing the model puts in evidence that i) the coefficients $\Pi^n_{CR,rc}(L)$ relating the observables to the global financial uncertainty factor GFU are subject to restrictions involving coefficients at different levels of the hierarchical framework, and that ii) time-varying intercepts $\alpha_{CR,rcnt}$ are naturally modeled in this framework.

C: DHFM estimation with unbalanced panels

We estimate the following four-level dynamic factor model:

$$\begin{aligned} Z_{rcnt} &= \lambda^n_{C,rc}(L)\, C_{rct} + e_{Z_{rcnt}} \\ C_{rct} &= \Lambda_{R.rc}(L)\, R_{rt} + e_{C_{rct}} \\ R_{rt} &= \Lambda_{GFU.r}(L)\, GFU_t + e_{R_{rt}} \\ \Psi_{GFU}(L)\, GFU_t &= e_{GFU_t} \end{aligned} \tag{3}$$

where Z_{rcnt} is the monthly volatility at time t for variable n and country c belonging to region r, with zero mean and standardized to have unit variance. GFU_t denotes the common factor, $\Lambda_{GFU.r}(L)$ is the distributed lag of loadings on the common factor, $e_{R_{rt}}$ is the region-specific variation, R_{rt} is the $(k_R \times 1)$ vector of region-specific factors, where k_R denotes the number of regions, $\Lambda_{R.rc}(L)$ is the distributed lag of loadings on the region-specific factors, $e_{C_{rct}}$ is the country-specific variation, C_{rct} is the $(K_{Cr} \times 1)$ vector of country-specific factors, where K_{Cr} denotes the number of countries in region r, $\lambda^n_{C,rc}(L)$ is the distributed lag of loadings on the country-specific factors, and $e_{Z_{rcnt}}$ is the series specific variation. We then assume that the idiosyncratic components, the country-specific, the region-specific, and the global factors are stationary, normally distributed autoregressive processes of order $q_{Z_{rcn}}, q_{C_{rc}}, q_{R_r}$, and q_{GFU}

$$\begin{aligned} \psi_{GFU}(L)\, GFU_t &= \epsilon_{GFU,t}, \quad \epsilon_{GFU,t} \sim N\left(0, \sigma^2_{GFU}\right) \\ \psi_{R_{rt}}(L)\, e_{R_{rt}} &= \epsilon_{R_{rt}}, \quad \epsilon_{R_{rtt}} \sim N\left(0, \sigma^2_{R_r}\right), \quad r = 1, \ldots, k_R \\ \psi_{C_{rc}}(L)\, e_{C_{rct}} &= \epsilon_{C_{rct}}, \quad \epsilon_{C_{rct}} \sim N\left(0, \sigma^2_{C_{rc}}\right), \quad c = 1, \ldots, k_{rC} \\ \psi_{Z_{rcnt}}(L)\, e_{Z_{rcnt}} &= \epsilon_{Z_{rcnt}}, \quad \epsilon_{Z_{rcn,t}} \sim N\left(0, \sigma^2_{Z_{rcn}}\right), \quad n = 1, \ldots, k_{rcN} \end{aligned}$$

where k_R is the number of regional blocks, k_{rC} is the number of countries in region r, k_{rcN} is the number of series for country c belonging to region r. In principle, the lag order can differ across individual series, country subblocks, and regional blocks. Our estimation follows the MCMC algorithm proposed by Moench, Ng, and Potter (2013), and generalizes it to allow for missing observations and unbalanced datasets. The estimation steps are the following:

Let $\mathbf{\Lambda} = (\Lambda_C, \Lambda_R, \Lambda_{GFU})$, $\mathbf{\Psi} = (\Psi_{GFU}, \Psi_R, \Psi_C, \Psi_Z)$, and $\mathbf{\Sigma} = (\Sigma_{GFU}, \Sigma_R, \Sigma_C, \Sigma_Z)$. The steps of the estimation procedure are as follows:

1. Organize the data into blocks (regions) and subblocks (countries) to yield Z_{rct}, with $r = 1, \ldots, k_R$, $c = 1, \ldots, k_{rC}$. Get initial values for $\{C_t\}, \{R_t\}, \{GFU_t\}$ using the EM algorithm by Banbura and Modugno (2014). Use these to produce initial values for $\mathbf{\Lambda}$, $\mathbf{\Psi}$, and $\mathbf{\Sigma}$.

2. Conditional on $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Sigma}$, $\{R_{rt}\}$ and the data Z_{rct}, draw $\{C_{rct}\}$ $\forall r$ $\forall c$.

3. Conditional on $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Sigma}$, $\{C_{rt}\}$ and $\{GFU_t\}$, draw $\{R_{rt}\}$ $\forall r$.

4. Conditional on $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Sigma}$, and $\{R_t\}$, draw $\{GFU_t\}$.

5. Conditional on $\{GFU_t\}, \{R_t\}$, and $\{C_t\}$ draw $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Sigma}$.

6. Return to 2.

To take into account the dependence among the factors at different levels, we adopt the same Kalman filter algorithm as in Moench, Ng, and Potter (2013). Following Moench, Ng, and Potter (2013), we assume a standard normal distribution as prior distribution for all factor loadings Λ and for all autocorrelation coefficients Ψ, and an inverse chi-square distribution with 4 degrees of freedom and scale parameter equal to $\sqrt{0.01}$ for the variance parameters.

For our baseline scenario, after discarding the first 15,000 as burn-in, we take another 15,000 draws, storing every fifteenth, so that our results are obtained on the stored 1,000 draws.

D: Comparison with Principal Components

To assess whether controlling for the block-level variations is important, we compare the information carried by the "global" factor estimated by principal components $\tilde{F}_t$ with the GFU factor extracted using the DHFM model in (1). We proceed as follows. First, we regress the principal component $\tilde{F}_t$ on GFU_t, and save the residuals $\tilde{e}_t$. These residuals can be interpreted as variations that are considered common when the global factor is estimated via principal components, but not when it is estimated using the hierarchical model. Then, we regress $\tilde{e}_t$ on each regional factor to check whether these residuals can be explained by our estimated regional components. Table A1 reports the estimated coefficient, $\widehat{\beta}_{rt}$, and the associated p-value for each of the five estimated model. We find that the North America, Oceania, and Asia block specific factors are all significant, at any conventional level. When we investigate in a similar way the role of country-specific factors, again we find evidence that also country specific factors explain these residuals (results not reported here but available upon request). We interpret this evidence as supportive of the relevance of controlling for region and country specific dynamics to correctly quantify the global factor.

E: Regional and country-specific factors

Even though the focus of our analysis is the estimation of a global financial uncertainty index obtained after controlling for co-movements that are specific to a given region or country, a by-product of the DHFM are region- and country-specific uncertainty measures. In this section we report some selected regional and country specific uncertainty indices, discuss their dynamics, and provide a comparison with the global uncertainty measure. Figure A2 plots each of the regional components against the global index. It is worth noticing that the regional uncertainty indices follow heterogenous dynamics: while uncertainty in some regions (e.g. Europe and Oceania) display high correlation with the global component, others (Latin America, in particular) show a more prominent idiosyncratic behavior. Prominent examples are: the 2011 sovereign debt crisis in Europe which determined a large increase in uncertainty both at a regional and at a global level, and as such can be classified as a "global" event in terms of financial uncertainty; the 1997 Asian financial crisis, which has triggered an increase in both the regional and the global component, but with a relatively stronger impact on the regional one; the Latin American currency crises of the early 1990s, which are reflected in a remarkable increase of financial uncertainty within the region, but triggered no noticeable spike at a global level.

A similar heterogenous pattern is evident from the country specific components (see Figures A3 and A4). While uncertainty in some countries (e.g. the US, the UK, Germany, Australia) is highly correlated with the global component, in some other countries (Argentina and China, in particular) financial uncertainty displays barely any correlation with the global component. Telling examples of this heterogenous dynamics are: the 1992 exchange rate crisis in Italy and the 2011 sovereign debt crisis in Greece, which are both events that triggered an increase in uncertainty at a global level but not as much as at a country-specific level; the 1994 Mexican currency crisis, the 2001 debt default in Argentina, and the Chinese economic reforms of the early 1990s, which are all events that triggered enormous spikes in financial uncertainty at a country level, but barely any change in global uncertainty.[1]

[1] An important remark is that, though the main source of heterogeneity among euro area countries is due to the country-specific volatility of stock prices and government bond yields, the exchange rate volatility after the introduction of the euro is not necessarily the same across countries. The reason is the following. Our monthly realized volatilities are constructed starting from daily data. In a given month, data for two different euro area countries are not necessarily available for the very same days.

F: VAR analysis: Data and IRFs

Figure A5 plots the data used in our VAR analysis. Figure A6 plots the impulse responses to the three shocks we work with in our empirical analysis.

G: GFU: The role of COVID-19 observations

Figure 2 in the paper reports our estimate of the GFU factor obtained by working with the sample July 1992-May 2020. Obviously, the last three months of this sample (March-May 2020) are associated with extreme realizations of stock market returns and asset returns more in general. These observations could in principle negatively affect the consistency of our GFU estimates, which are obtained with a fixed-coefficient model (although, as shown in Section B of this Appendix, the model can be re-written in order to put in evidence the time-varying intercepts linking our observables with the GFU factor). Figure A7 contrasts our baseline GFU estimate with the one obtained with pre-COVID19 observations, which we used in a previous version of the paper (sample: July 1992-June 2019). Bottom line - in the common sample, the two estimates coincide. Apart from the time-varying intercepts, which could help capture the different volatilities in the last three months of the sample, our explanation for the irrelevance of the COVID-19 observations on the GFU estimate in the pre-COVID19 sample is the data we use, i.e., monthly volatilities that are computed on the basis of daily returns that are corrected by a month-specific mean. In other words, the data processed by the DHFM are constructed by considering a monthly mean of the various returns we use that already accounts for outliers.

H: Role of different seeds

Baumeister and Hamilton (2020) stress that the seed one sets for initializing the algorithm used to draw different rotations of the Cholesky-VAR variance-covariance matrix can play a role when it comes to producing moments such as impulse responses to identified shocks, or peak responses across different retained models, and so on. Figure A8 plots the summary of our main results in the paper conditional on four different seeds. Our results turn out to be pretty robust to changes in the seed set for the simulations that produce our baseline results.

The reason is that data (including exchange rate data) are not reported for public holidays, and public holidays differ among countries.

I: Role of Haar measure and orthonormal matrices

The orthonormal $\mathbf{Q}$ matrices we work with to generate candidate impulse vectors that are then assessed against our identification restrictions are drawn from a distribution that is uniform with respect to the Haar measure over the set of such $\mathbf{Q}$ matrices. As stressed by Baumeister and Hamilton (2020), this does not necessarily imply that the moments of interest are also uniformly distributed across the models $\mathbf{B}$ consistent with the data. Hence, it is important to check how the moments of interest look like when one considers all models consistent with the data before imposing the identification restriction. This way of proceeding naturally provides us with an assessment of the contribution of our restrictions too. Figure A9 plots the moments of interest in absence of the imposition of any of our identification restrictions. The Figure clearly points to the role of our identification restrictions in dramatically narrowing down and tilting the set of impulse responses to the negative territory as far as the responses of the global financial cycle and the world output are concerned. The set of responses of GFU itself substantially shrinks after the imposition of our restrictions.[2] The effect of our restrictions on the empirical distribution of peak (negative) responses of world output is also quite noticeable, with the figures reported for the models suggesting a positive response of output to a GFU shock being those of the very last horizon considered. Finally, and interestingly, the scatter plot involving the world output loss and the global financial cycle deterioration actually points to a positive correlation even in absence of our identification restrictions. However, the cloud of points is much more condensed when imposing our restrictions, and the estimated slope of the interpolating straight line is clearly steeper.

References

Banbura, M., and M. Modugno (2014): "Maximum likelihood estimation of factor models on data sets with arbitrary pattern of missing data," *Journal of Applied Econometrics*, 29(1), 133–160.

Baumeister, C., and J. D. Hamilton (2020): "Drawing Conclusions from Structural Vector Autoregressions Identified on the Basis of Sign Restrictions," *Journal of International Money and Finance*, forthcoming.

[2] The technical restriction requiring that the B matrices feature positive elements of the main diagonal is left active while producing the plots in the lower panels of Figure A9. This is the reason why, on impact, all responses of GFU to a global financial uncertainty shock are positive.

Moench, E., S. Ng, and S. Potter (2013): "Dynamic Hierarchical Factor Models," *Review of Economics and Statistics*, 95(5), 1811–1817.

Regional factor	$\widehat{\beta}_r$	p-value	R^2
North America	0.145	0.000	0.076
Europe	0.008	0.695	0.000
Oceania	0.099	0.001	0.035
Latin America	0.069	0.487	0.000
Asia	-0.045	0.048	0.012

Table A1: **Correlation with regional factors.**

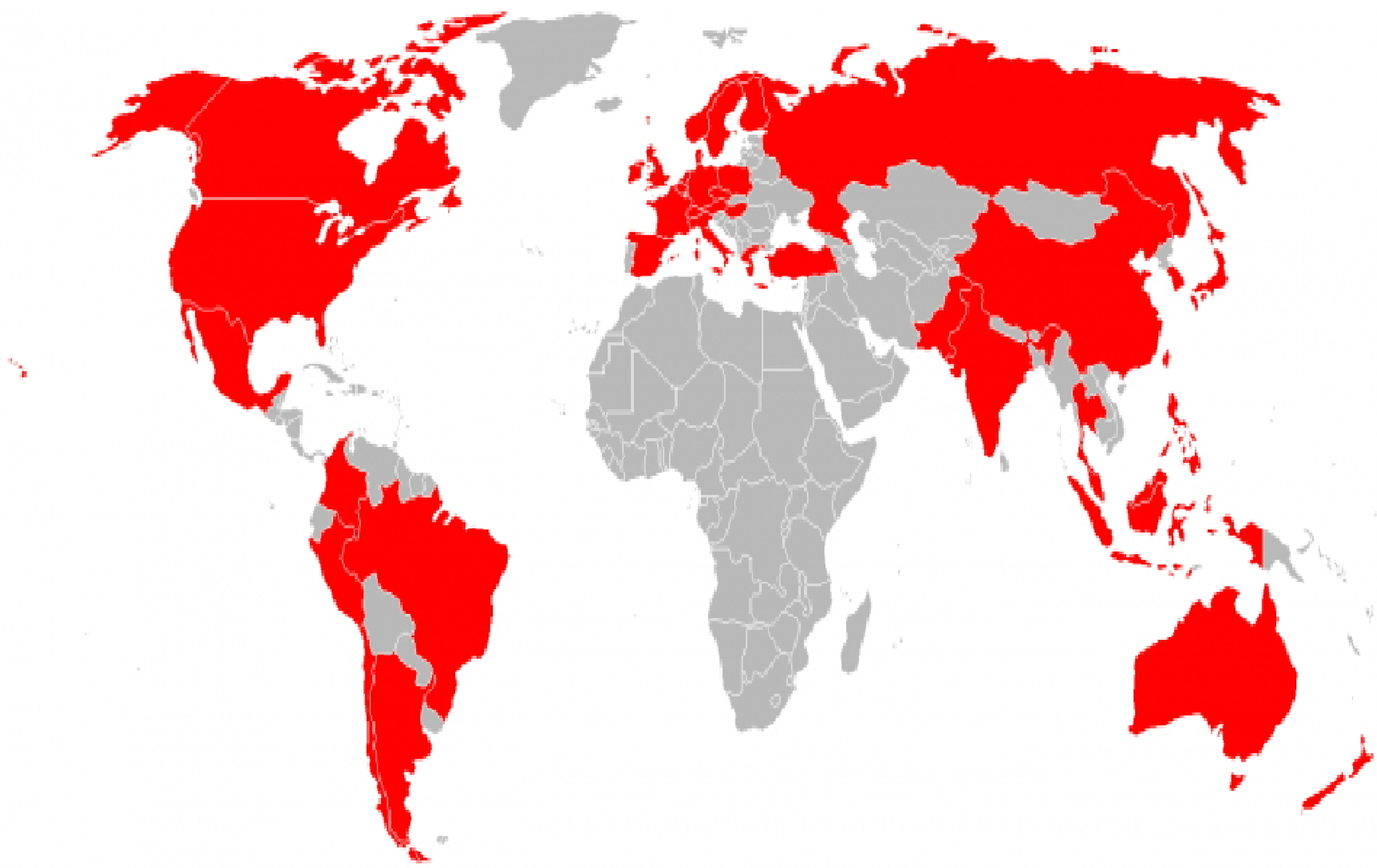

Figure A1: **Our dataset: Geographical coverage.** Countries included in our dataset identified in red.

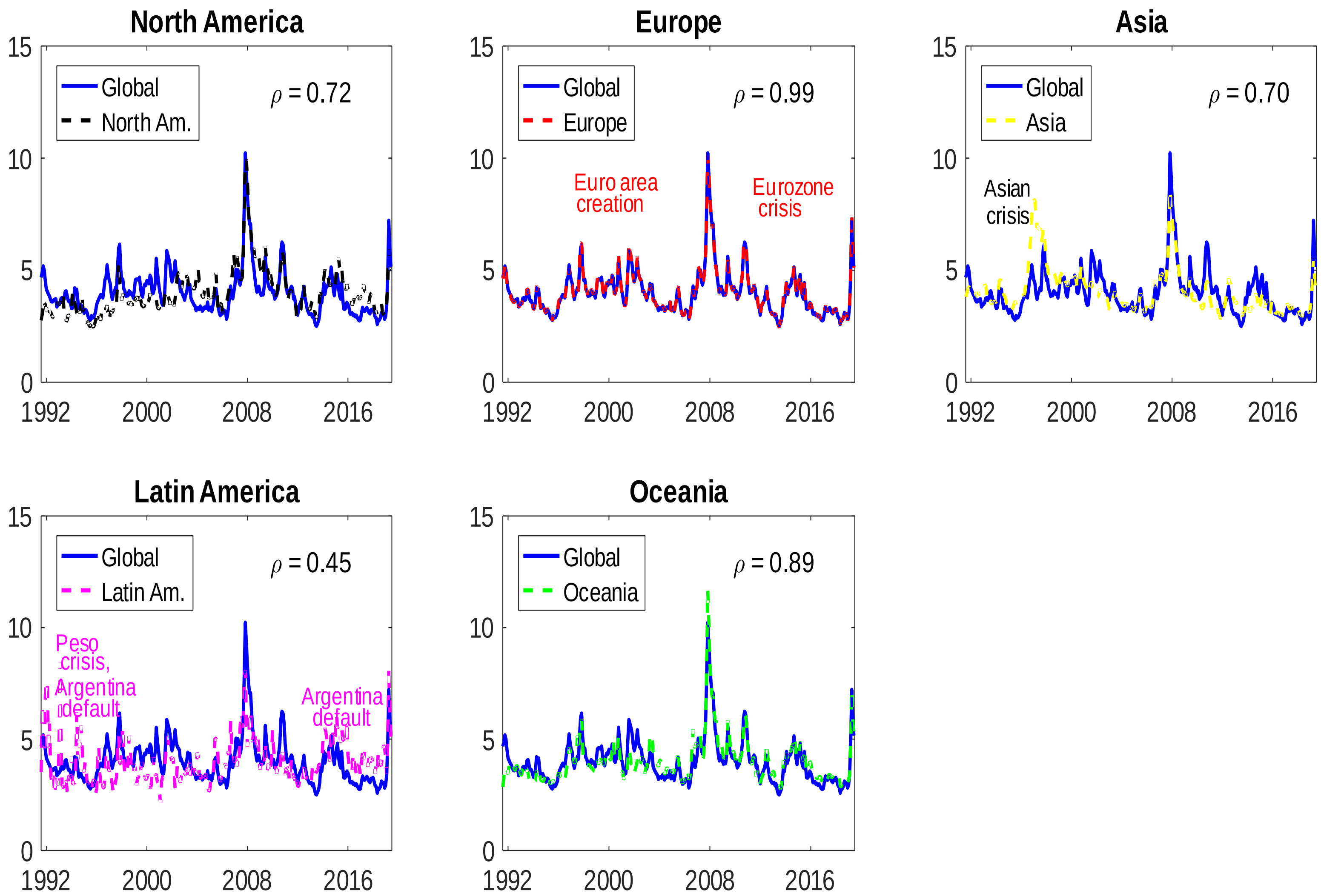

Figure A2: **Regional factors.** Construction of the series explained in the text.

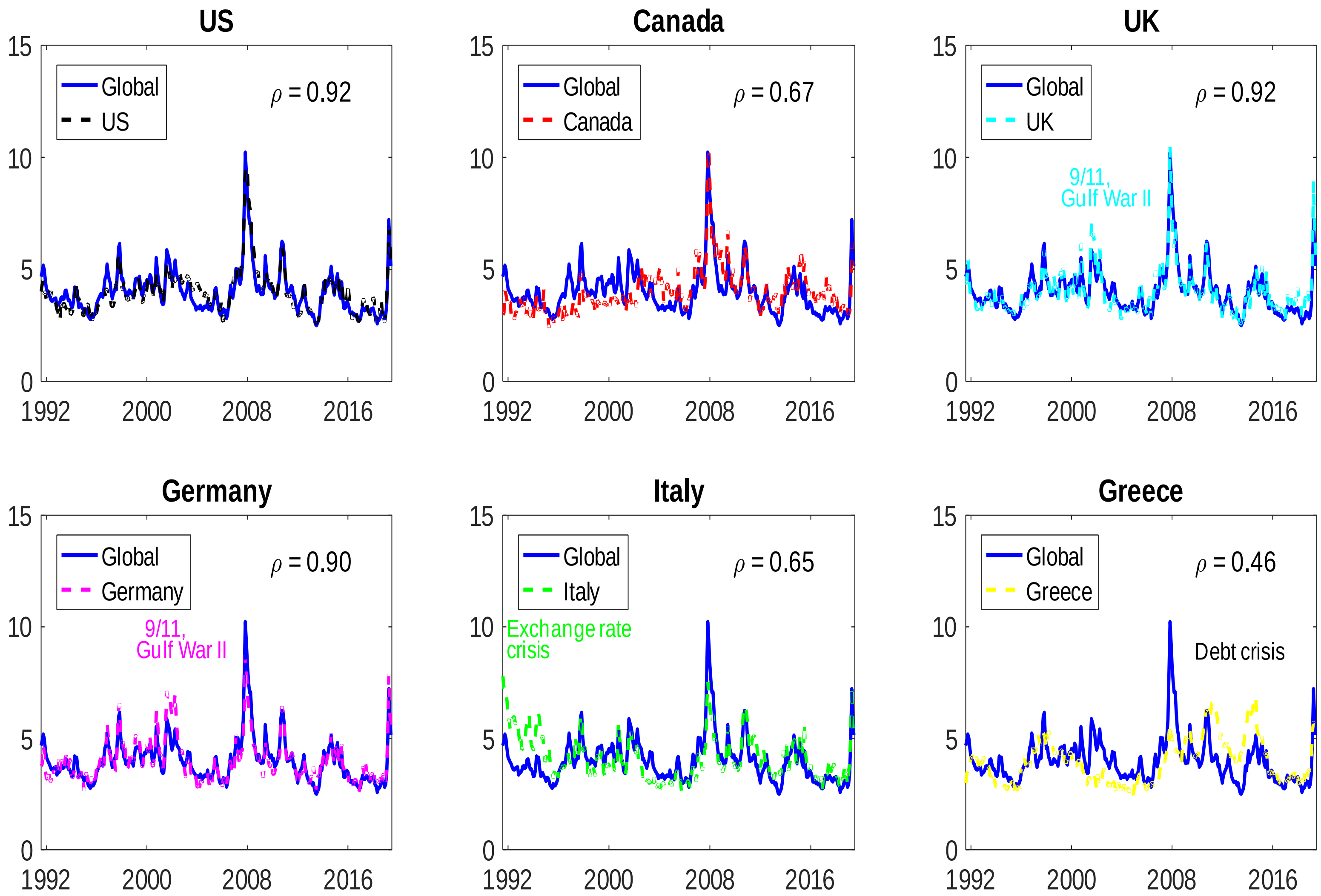

Figure A3: **Country-specific factors (selected countries).** Construction of the series explained in the text.

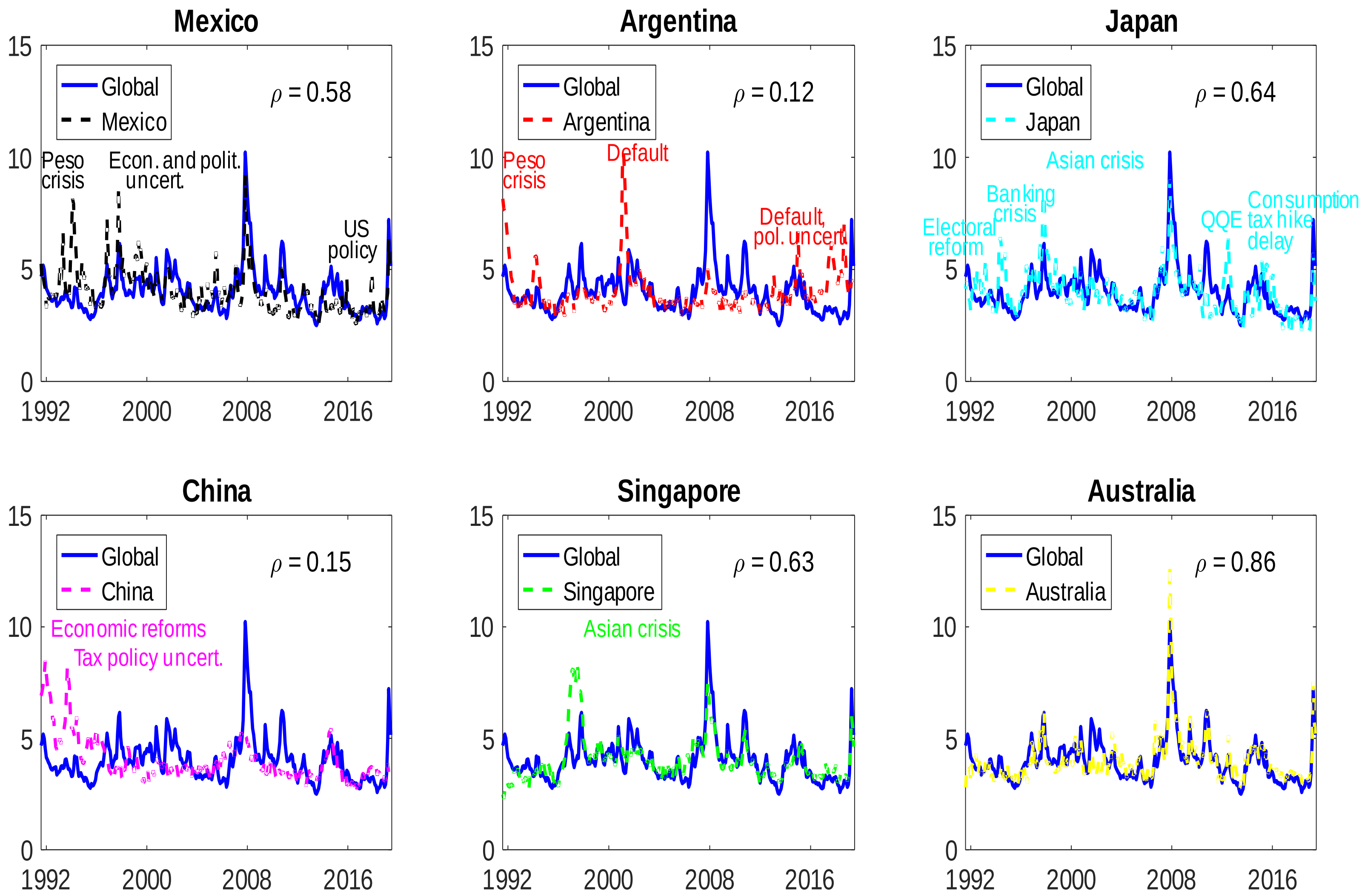

Figure A4: **Country-specific factors (selected countries).** Construction of the series explained in the text.

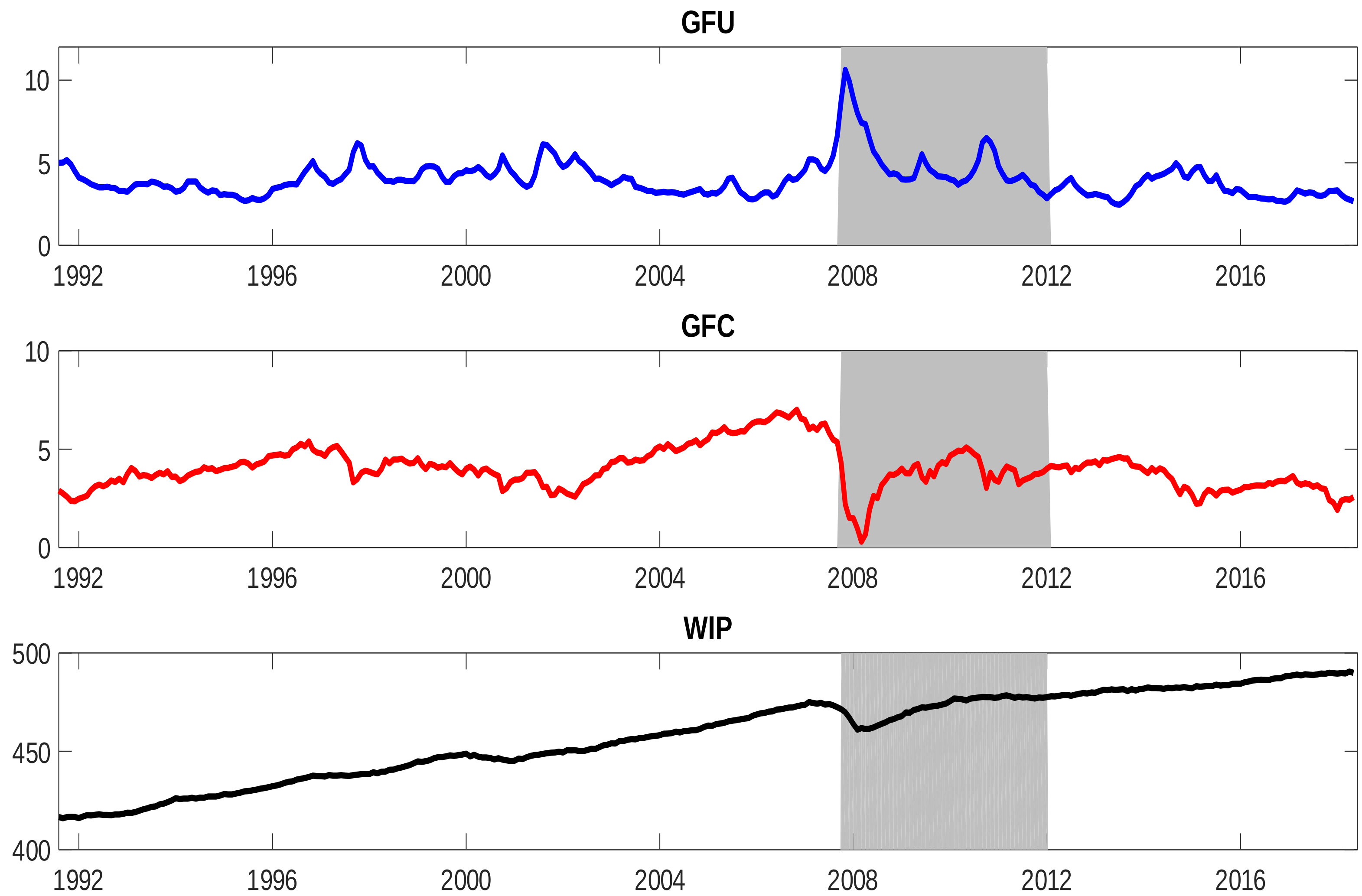

Figure A5: **VAR analysis: Series.**

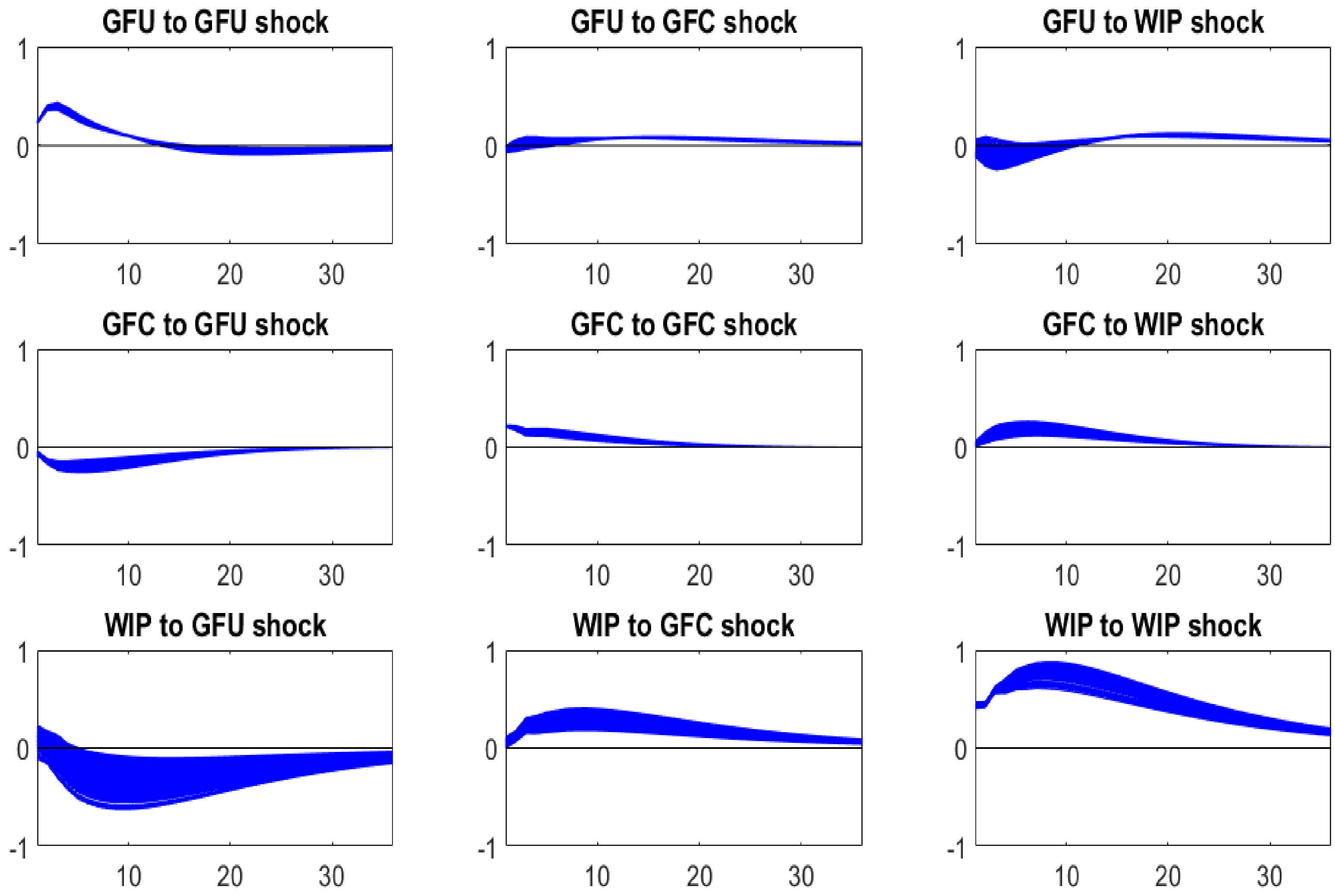

Figure A6: **Impulse Responses to all shocks.** Sample: 1992M7-2012M12. Responses to a one standard deviation shock. Identification of the shock achieved by imposing the mix of event and sign restrictions indicated in Table 1.

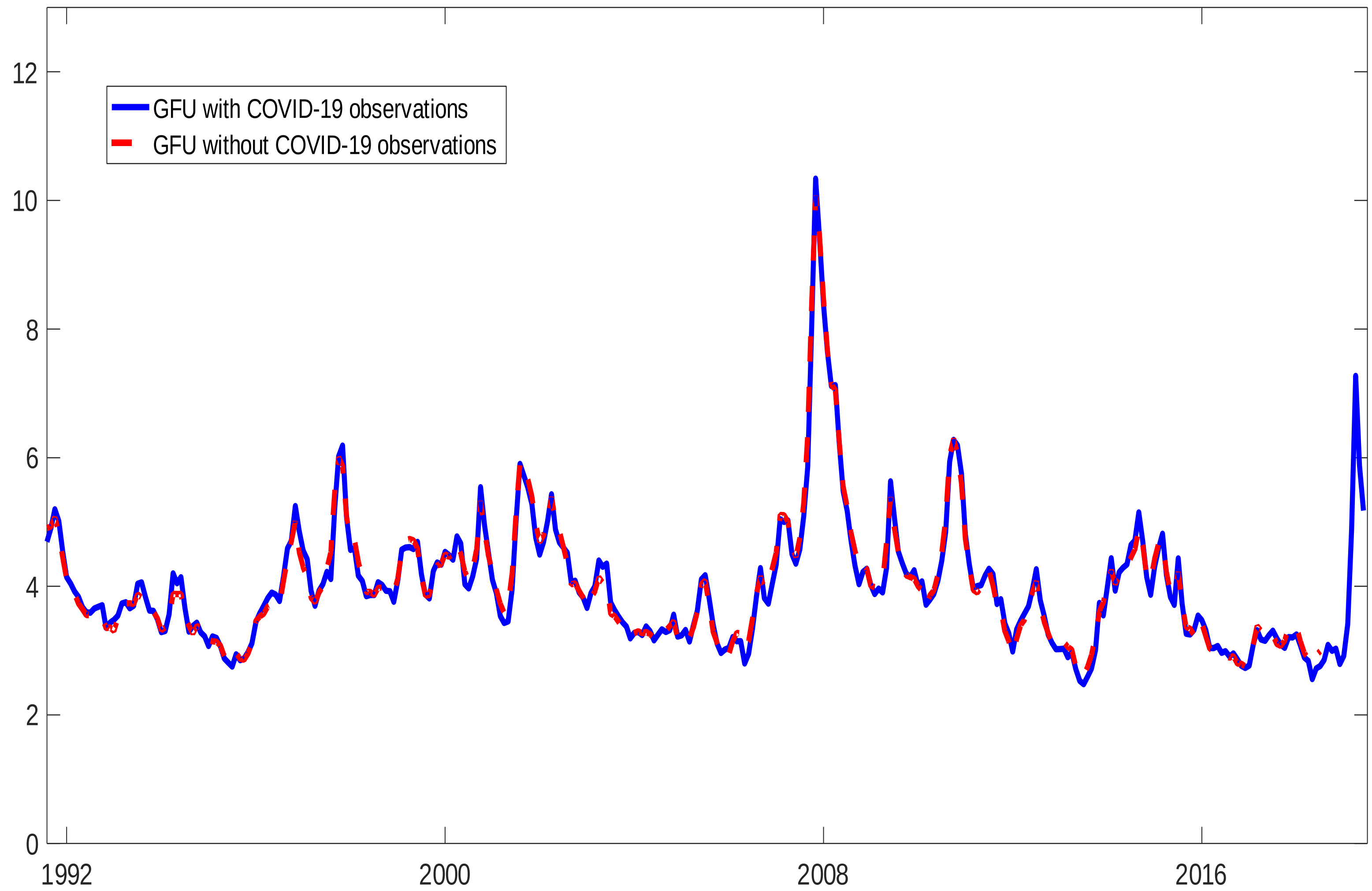

Figure A7: **Global Financial Uncertainty factor: Role of COVID-19 observations.** Factors estimated with the very same dynamic hierarchical factor model over two different samples, i.e., 1992M7-2019M6 (without COVID-19 observations) vs. 1992M7-2020M5 (with COVID-19 observations). Factor standardized over the common sample 1992M7-2019M6.

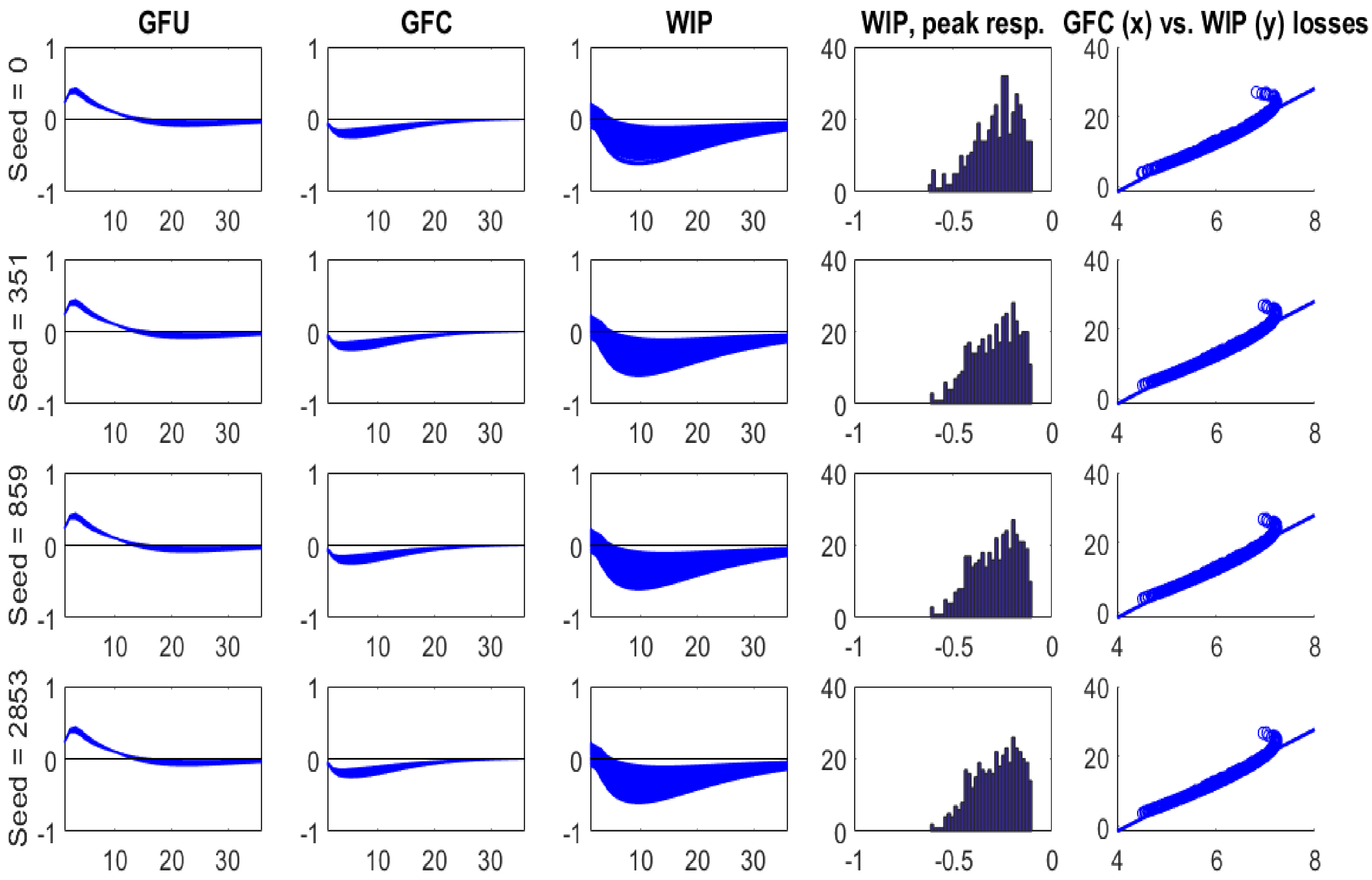

Figure A8: **Macroeconomic Implications of GFU Shocks: Role of Different Seeds.** Impulse responses to a GFU shock (first three columns), peak responses of world industrial production across retained models (fourth column), and scatter plot of WIP loss vs. GFC loss (fifth column) across different seeds initializing our simulations. Seed = 0: Baseline case.

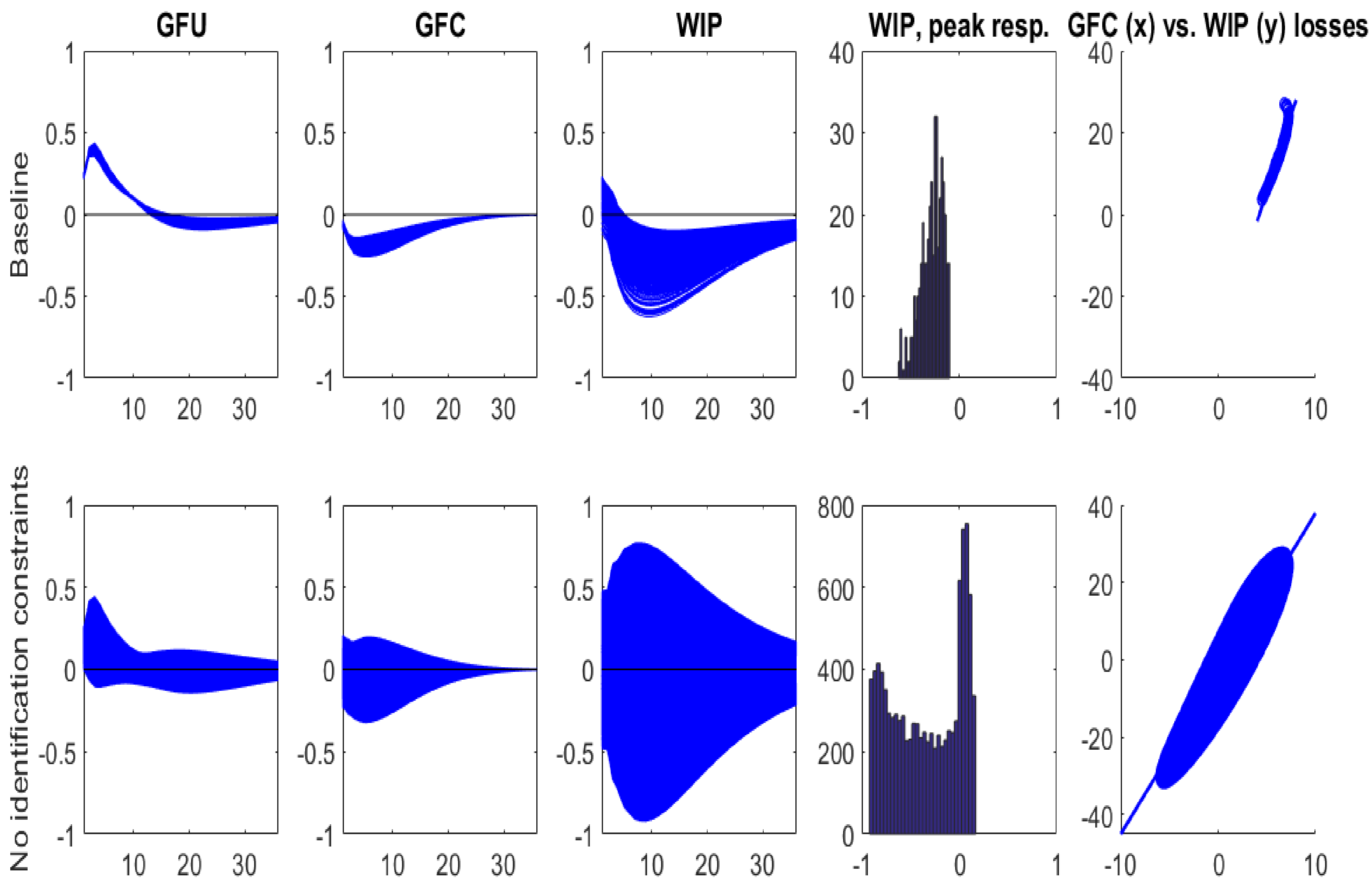

Figure A9: **Impact of the Haar Distribution on Our Results.** Upper panels: Baseline results obtained by imposing the identification restrictions as explained in the text. Lower panels: Moments implied by all rotation matrices without imposing any identification restriction. Moments in the lower panel conditional on just 10,000 (all retained) draws to facilitate the production of the figure.