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Abstract

In this paper, we analyse the effects of a shock to global financial uncertainty and risk aversion on real economic activity. To this end, we extract a common factor from the realised volatilities of about 1,000 risky asset returns from around the world. We then study how shocks to the factor affect economic activity in 44 advanced and emerging small open economies by estimating local projections in a panel regression framework. We find that the output responses are quite heterogeneous across countries but, in general, negative and persistent. Furthermore, the effects of shocks to the global factor are stronger in countries with a higher degree of trade and/or financial openness, as well as in countries with a higher level of vulnerabilities.

Key words: Global uncertainty, global risk aversion, global financial cycle, small open economies.

JEL classification: F41, E32, F65.

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1 Introduction

Over the last 30 years, we have witnessed a dramatic increase in financial globalisation. In light of this change in the global financial system, a vast literature has documented the growing importance of cross-country financial flows and holding (e.g. Lane and Milesi-Ferretti, 2007) and postulated the existence of a global financial cycle, which has the potential of morphing the Mundellian trilemma into a dilemma (Rey, 2015).

While this literature has mainly focused on studying the drivers of the global financial cycle (Miranda-Agrippino and Rey, 2015; hereafter MA-R) or its impact on capital flows (see for example Forbes and Warnock, 2012, Fratzscher, 2012, and Milesi-Ferretti and Tille, 2011), evidence on its real consequences for small open economies around the world is scant. In this paper, we fill this gap and seek to empirically quantify the effects of changes in global financial risk and uncertainty on economic activity (industrial production) for a wide range of small open economies, 27 advanced (AEs hereafter) and 17 emerging market economies (EMEs hereafter). In order to do so, we first construct a dataset of about 1000 risky asset returns, traded in major global markets, finding that one single factor, which we label as the global financial risk and uncertainty index (hereafter GFRUi), explains around 51 per cent of the variation in global risky assets' realised volatility. Second, we quantify the effects of shocks to the GFRUi on economic activity in 44 small open economies. To this end, we estimate Local Projections à la Jorda (2005) with panel regressions and find that a shock to global financial risk and uncertainty significantly worsens real economic activity in a persistent manner. These effects are rather heterogeneous across countries. We find a stronger impact in countries with higher vulnerabilities (e.g. high debt levels) and those with higher trade openness and financial integration. When we estimate the local projections with two-stage least squares, using variations in the gold price as an external instrument for uncertainty, we find our baseline results to be confirmed. The effects found in our main exercise are also robust to other robustness checks, such as the inclusion of further controls (oil prices and euro area short-term interest rate) in our baseline model specification, as well as changing the number of lags of our regressions.

From a methodological point of view, this work is closely related to the literature on the global financial cycle (e.g. Bruno and Shin, 2015; Cerutti et al., 2014; Borio, 2012). In particular, the construction of the GFRUi follows MA-R, though we consider a different and broader dataset and we focus on second moments. Specifically, we estimate the global factor from the realised variance of global assets' returns rather than from the first difference of stock prices. MA-R and Coeurdacier et al. (2011) document with an SVAR and a Proxy-SVAR that US monetary policy shocks are among the main drivers of the global financial cycle. We depart from the previous literature and these last two papers in particular, in that we do not look at the causes of the global financial cycle but rather at its consequences. More specifically, our main contribution is analysing how global financial uncertainty affects different small open economies and identifying the key transmission channels.[1]

Since the GFRUi is a measure of global uncertainty and risk aversion, this paper is also strongly related to the strand of the macroeconomic literature on the economic effects of uncertainty shocks. After the seminal paper by Bloom (2009), a growing body of literature has flourished (e.g. Backus et al., 2015; Born and Pfeifer, 2014; Bachmann et al., 2013; Fernandez-Villaverde et al., 2015; Basu and Bundick, 2017; Bonciani and van Roye, 2016) and has investigated how uncertainty shocks could generate business cycle fluctuations both with empirical and theoretical frameworks. From an empirical point of view, the literature has found that increases in

[1] In this paper, we show how certain measures of openness, integration and vulnerabilities are correlated with countries' exposure to the measure in question, thus exacerbating responses to its changes. We do not genuinely identify the mechanism through which our global measure of risk and uncertainty has real implications worldwide. Specifically, it is outside the scope of this paper to identify the way its movements affect local demand components through e.g. changes in local financial conditions or local stochastic discount factors.

uncertainty cause significant downturns in economic activity. This result has been found using various measures of uncertainty such as financial volatility indexes (Bloom, 2009), macroeconomic uncertainty measures (Jurado et al., 2015; Rossi and Sekhposyan, 2015) or political uncertainty news-based indexes (Baker et al., 2016; Caldara and Iacoviello, 2016). All papers mentioned above have focused on the US, while the literature on the international transmission of uncertainty shocks is far more scarce. Fernandez-Villaverde et al. (2011) use a small open economy model and find strong negative effects on economic activity of interest rate volatility shocks. Mumtaz and Theodoridis (2015) analyse how uncertainty shocks spill over internationally through the trade channel in a two-country New Keynesian framework. Noteworthy empirical work is the one by Carrière-Swallow and Céspedes (2013) who analyse the effects of US uncertainty shocks on EMEs and document the flight-to-quality channel to be particularly relevant to explain the large effects in EMEs. Cesa-Bianchi et al. (2019) show that country-specific volatility shocks have moderate economic effects, once they control for global growth and global financial conditions. In a recent paper, Crespo Cuaresma et al. (2017) study the effects of global uncertainty on $G7$ countries and find these to be much more persistent than previously highlighted in the literature. The use of panel local projections represents a strong difference from the papers above, as we consider our methodology to be more robust to potential model misspecifications than standard VARs. Moreover, we exploit both the time-series and the cross-sectional information contained in our panel, differently from Carrière-Swallow and Céspedes (2013), who simply run country-by-country VARs. Additionally, our empirical approach facilitates the study of state-dependent responses to the shock variable, allowing us to identify country characteristics that affect the transmission of the shock. The remainder of the paper is structured as follows: in section 2, we describe the empirical strategy adopted by first presenting the data and the statistical methodology employed to estimate the GFRUi (section

2.1) and then by discussing the model used in the empirical analysis (section 2.2). In section 3, we analyse the results; in section 4, we conclude the paper with some final remarks.

2 Empirical strategy

Our empirical approach is laid out in three different sections. In the first one, we define the strategy adopted to obtain the GFRUi and the data we used. In the second, we explain how we identify global financial uncertainty and risk shocks. Last, we show how the GFRUi affects small open economies and analyse the key transmission channels of the identified shock.

2.1 The Global Financial Risk and Uncertainty Index

The dataset used to derive the GFRUi consists of a large panel of around 1000 series of financial stock prices from North America, Asia, Europe, Latin America, and Oceania, including indexes specifically designed to track developments in the commodity and banking sector. Our aim is to collect a vast and heterogeneous panel of financial series which approximates the breadth of global financial markets and provides an encompassing account of the different economic sectors.[2] The main source of our data is Thomson Reuters Datastream, which produces market indexes for the vast majority of countries with a developed financial sector, additionally classifying them by economic, business sector and industry group.[3] Further details on the series contained in our dataset can be found in Table 1. We collect daily data on a monthly basis from January 1991 to December 2016. For each asset price series S_n we first compute daily log returns $s_{n,r} = ln(S_{n,r}/S_{n,r-1})$ for each day r and then the realised variances as the sum of the square log-returns within each month t. We then calculate the realised volatility by taking the square root of the realised variance.

[2]Following MA-R, the series are chosen by taking a representative market index for each financial market and related components.

[3]An additional advantage of using this data provider is that we can construct a balanced panel for the period of interest. Therefore, our results will not be biased by the imputation of missing observations.

$$\sigma_{n,t} = \sqrt{\sum_{k=1}^{K} (s_{n,k})^2} \quad \text{for } k = 0, 1, 2, ..., K \quad \textit{days in the month} \tag{1}$$

We define the GFRUi as the first principal component of the realised volatilities. Before extracting the factor, the individual realised volatility series are stationarised, while outliers are removed following the procedure used by Eickmeier et al. (2014).[4] The GFRUi explains 51.2% of the variation in global risky assets' realised volatility and hence summarises changes in global risk and uncertainty.[5] This becomes especially apparent in Figure 1, where we plot the GFRUi series against the NBER recessions and some important economic and political events. As can be seen from the figure, the GFRUi tends to spike during events that caused turmoil in financial markets, such as the fall of Lehman Brothers or the 9/11 terrorist attack.

Comparing the GFRUi with Other Measures of Uncertainty As we explained above, the GFRUi is defined as the common realised volatility of a large panel of risky-assets returns, which reflects movements in aggregate uncertainty. To corroborate this interpretation about the nature of the GFRUi, we compare it with other commonly used measures of uncertainty: (i) measures of Economic Policy Uncertainty (Baker et al., 2016) for China, Europe, Japan, USA and the World; (ii) the Geopolitical Risk Index by Caldara and Iacoviello (2016); (iii) US financial uncertainty and macroeconomic uncertainty by Ludvigson et al. (2015) and Jurado et al. (2015); (iv) the S&P500 implied volatility measure, VIX. In Figure 2, we display pairwise comparisons of the GFRUi (blue line) with each alternative uncertainty indicator (black line).

[4] Outlier adjustment entails replacing data with absolute median deviations larger than 3 times the interquartile range with the median value of the 5 preceding observations.

[5] It is interesting to note how one global factor explains such a large share of the common variation in risk and uncertainty. MA-R find that one factor explains roughly 20% of the common variation in the returns of risky assets. Our result shows that the realised volatilities of global assets returns tends to co-move more than the returns themselves.

For comparative purposes, all measures are standardised to have mean zero and unit standard deviation. Most measures (except the Geopolitical Risk index) show a peak in 2008 in conjunction with the fall of Lehman Brothers, which triggered a global financial turmoil and a strong rise in uncertainty. The GFRUi shows a particularly strong correlation with the VIX and the measure of US financial uncertainty (correlation of 85% and 76.3%), highlighting the importance of the US in global financial markets. Our measure of Global Risk and Uncertainty also shows a significant correlation with US macroeconomic uncertainty (correlation of 67.4%) and US economic policy uncertainty (42%). The strong correlation with the economic policy uncertainty measure is consistent with the finding in Gala et al. (2018), which shows how measures of political stability and confidence in economic policy can predict international stock returns. The GFRUi also strongly co-moves with Japan's economic policy uncertainty (50.5%). In a milder way, the GFRUi also correlates with Global and European economic policy uncertainties (14.4% and 11%), while the degree of co-movement with the geopolitical uncertainty index (3%) and Chinas' EPU (0.5%) are negligible.

2.1.1 The Local Projection Method for Panel Data

In order to estimate the effects of an increase in the GFRUi, we use the local projection methodology developed by Jorda (2005), extended to a panel data context. The use of local projections has several advantages over standard VARs. In particular, impulse responses are usually estimated from the Wold representation of the VAR process, which involves a two steps procedure: first, the model needs to be estimated; second, the parameter estimates need to be inverted. This is only justified if the model is not misspecified, i.e. the model is actually the true data generating process (Jorda, 2005). The local projection technique combines the two steps mentioned above into one and is more robust to model misspecifications, as it does not impose dynamic restrictions on the IRFs. Other advantages of this methodology are that it conveniently allows for non-linearities in the response function and its flexibility enables us to study state-dependent responses without large modifications to our baseline model.

To illustrate the basic idea behind the local projections methodology, consider the definition of impulse response by Koop et al. (1996), that abstracts from any reference to the data generating process (DGP hereafter):

$$IRF(t,h,d_i) \equiv \mathbb{E}\left[Y_{t+h}|v_t = d_i; S_t\right] - \mathbb{E}\left[Y_{t+h}|v_t = 0; S_t\right] \quad \text{for } h = 0,1,2,...,H \tag{2}$$

where: $E[\cdot|\cdot]$ is conditional expectation function; t is the current period and h the time horizon; the Y_t is a vector of dimension $n \times 1$; S_t is the vector of lags of Y_t and other controls; v_t is the vector of reduced form errors; d_i is the identified structural shock. The IRF as defined in equation (2) is the best multi-step prediction of Y_{t+h} given S_t. Best, in that it minimizes the mean squared error. Unless the VAR is the DGP, recursively iterating on the estimated VAR model is not an optimal way of computing the IRFs. Direct forecasting models, re-estimated for each h, produce better multi-step predictions. Our baseline panel regression to estimate local projections is given by (3):

$$\begin{aligned} Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \gamma_{i,h} Z_t + B_{i,h}^{Global}\left(L\right) X_{i,t}^{Global} + \\ B_{i,h}^{Local}\left(L\right) X_{i,t-1}^{Local} + C_h\left(L\right) Z_{t-1} + \varepsilon_{i,t+h} \quad \text{for } h = 0,1,2,...,H \end{aligned} \tag{3}$$

In the regression equation (3), $\alpha_{i,h}$ is the country i fixed effect, $Y_{i,t}$ is the dependent variable, $X_{i,t}^{Global}$ is a set of Global variable controls, described in subsection 2.2.1), contemporaneous to the GFRUi. $X_{i,t-1}^{Local}$ is a set of local variable controls, that enter the regression with a lag, and $\varepsilon_{i,t}$ is the error term for time $t+h$. $B_{i,h}^{Global}(L)$ and $C_{i,h}(L)$ are lag polynomials of order five, while $B_{i,h}^{Local}(L)$ is a lag polynomial of order four, so that all variables enter until lag $t-5$.[6] For example, projecting Y_{t+2} onto the variables on the right-hand side, we obtain the estimate $\hat{\gamma}_2$. This is the effect of an increase in Z_t (the GFRUi) on Y two-months ahead, that is orthogonal to the other variables on the right-hand side of the equation. Estimating H regressions for each response variable Y of interest gives us the sequence of "*local projections*". The estimated IRFs are therefore given by the sequence $(\hat{\gamma}_h)_{h=0}^{H}$, where an horizon of $H = 20$ months is considered. The main issue associated with the local projection method is the serial correlation in the error terms due to the successive leading of the dependent variable. It is therefore important to use HAC (heteroskedasticity and autocorrelation) robust standard errors. For these reasons, in our analysis, we use Driscoll-Kraay HAC standard errors that are appropriate in the context of panel regressions given that they also take into account cross-sectional dependence.

2.2 Estimating the impact of GFRUi shocks

2.2.1 Identification of Global Risk and Uncertainty Shocks

To identify shocks to global risk and uncertainty, we include the following controls in regression 3: contemporaneous and five lags of log trade-weighted average CPI, log trade-weighted weighted average Industrial Production,[7] Effective Federal Funds Rate (FFR), a Global Financial Conditions Index (GFCi) and lagged values of the GFRUi. More specifically, the CPI and IP measures are meant to control for global demand. The FFR is augmented with the shadow

[6] In the robustness section, we show that varying the number of lags does not significantly impact our results.
[7] Section C in the appendix describes in more detail how the CPI and IP indexes are constructed.

rate by Wu and Xia (2014) to better account for the US monetary policy stance during the period when the nominal interest rate had approached the zero lower bound.

Controlling for Global Financial Conditions We include an index of global financial conditions to control for movements in the global financial markets that are orthogonal to changes in risk and uncertainty. In order to construct the GFCi, we extract factors from the same returns dataset used for the GFRUi. Unlike the GFRUi that is the principal component of the realised volatilities, the GFCi is a factor extracted directly from monthly returns. Similarly as in MA-R, we define the GFCi as the cumulative sum of the first principal component, which explains 38% of the variation in global asset returns. Figure 3 displays the GFCi and compares it to the global financial factor estimated in MA-R. To highlight the high degree of correlation (86.5%), the two series are standardised to have mean zero and unit standard deviation over the sample considered. For the sake of conciseness, we leave the details about the construction of the GFCi index to the appendix D.

Since we include contemporaneous values in our regression, our identification strategy is equivalent to a Cholesky identification in a standard SVAR, in which the GFRUi is ordered below the other global variables. In other words, we assume that the GFRUi is contemporaneously affected by the other global shocks in the model, while shocks to the GFRUi do not have an effect on impact on the other global variables. This identification has been widely used in the literature (e.g. Jurado et al., 2015). In section 3.3, we will consider an alternative identification of the shocks, using variations in the price of gold as an instrument, following Piffer and Podstawski (2018).

2.2.2 Data Description

In order to estimate the effects of the GFRUi on the global economy, we collect macroeconomic data for the 44 countries listed in Table 2. The countries are classified between advanced and emerging economies consistently with the assessment provided by the International Monetary Fund in the World Economic Outlook Database.[8] We consider monthly data for industrial production (our proxy for output), CPI inflation and short-term interest rates, spanning from January 1991 until December 2016 (conditional on data availability). The data is obtained from national sources or international institutions (i.e. OECD or IMF (IFS)). Table 3 provides detailed information on sources, data availability and on the specific measure used for the short-term rates. The series for industrial production are taken from the World Trade Monitor of the CPB Bureau for Economic Policy Analysis. The production monitor covers currently 85 countries worldwide, which account for approximately 97% of global industrial production. The main advantages of using this dataset are that: (i) it includes time series from 1991 onwards for almost all countries considered in this paper;[9] (ii) it deals with various consistency issues concerning seasonal adjustments and industrial classification.[10]

[8]Some of the countries considered in this analysis have changed their status, from emerging to advanced economy, during the period considered. In that case, we attribute them to the income group where they have been for a longer time.

[9]The following countries are missing from the CPB database and are replaced with other sources: Chile (start 1991, source Sociedad de Fomento Fabril/Haver Analytics), Colombia (start 1991, source DANE/Haver Analytics) Malaysia (start 1991, source Department of Statistics, Malaysia/Haver Analytics, industrial production excluding construction) the Philippines (start 1991, source Datastream) South Africa start 1991, source BIS) Thailand (start 1998, source Datastream).

[10]Further details on the construction of the dataset can be found on the CPB website: https://www.cpb.nl/en/data.

2.3 Identification of the Transmission Determinants

As a baseline exercise, we first estimate panel local projections by running the fixed-effects regression described in equation (3). Additionally, we complement this exercise by running separate panel regressions for AEs and EMEs. Second, we run local projections country by country, to identify the response profile to the shock for each country in the sample. Third, we study the relevance of various transmission channels through which the GFRUi can potentially affect the economies under consideration. More in detail, we study whether the effects of increases in the GFRUi are heterogeneous across different economies, depending on the level of integration and openness and on their vulnerability.[11] To this end, we collect several indexes related to country openness and vulnerabilities (summarised in Table 4): **integration and openness** (i) de facto financial openness measured by foreign assets and liabilities over GDP; (ii) de iure financial openness measured by the Chinn-Ito index (Chinn and Ito, 2008), which accounts for regulatory restrictions to capital flows; (iii) capital flows restrictions based on the kai index (overall capital inflow restrictions) developed by Fernández et al. (2016); (iv) trade openness measured by the sum of exports and imports over GDP; **vulnerabilities** (v) composite country risk rating, (vi) financial risk rating and (vii) government stability from the International Country Risk Guide (ICRG); (viii) public debt relative to GDP, (ix) external debt relative to total debt and a measure of (x) debt sustainability constructed by the World Bank; (xi) the current account balance, (xii) IMF overall index of financial development and (xiii) domestic credit to the private sector relative to GDP as an additional measure of financial development. These indexes are all available for the sample period considered, except for the kai index which only starts in 1995. Data are collected using the database of international linkages (*IntLink*) developed by the ECB

[11] We chose the indicators for openness and vulnerability in line with Dedola et al. (2017) and Georgiadis (2016), who uses a similar classification to study the spillovers of a monetary policy shock in the U.S.

in the context of the International Linkages and Spill-overs Network,[12] and are converted into monthly figures by simply attributing the yearly figure to each month of the corresponding year. Additionally, following Iacoviello and Navarro (2018) we consider a measure summarising the degree of flexibility of the exchange rate vis-à-vis the U.S. dollar and an external vulnerability index constructed as an equally-weighted average of inflation (expressed as the year-on-year change of CPI), current account deficit, external debt less foreign reserves and foreign exchange reserves (the last three all expressed as a share of GDP).[13]

To analyse the role of each factor in amplifying the effects of the GFRUi, we deploy an empirical strategy in the spirit of Iacoviello and Navarro (2018). More specifically, for each characteristic we run the following regression:

$$
\begin{aligned}
Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \gamma_{i,h} GFRUi_t + \gamma_{i,h}^{v} \left(e_{i,t}^{v} GFRUi_t\right)^{\perp} + \\
\Gamma_h(L)\, GFRUi_{t-1} + B_{i,h}^{Local}(L)\, X_{i,t-1}^{Local} + B_{i,h}^{Global}(L)\, X_{t}^{Global} + \varepsilon_{i,t+h}. \quad (4)
\end{aligned}
$$

Hence, we augment the baseline regression (3) by an interaction term between the GFRUi and a function of the variable of openness or vulnerability, $e_{i,t}^{v}$. In particular, the latter is constructed in four steps: (i) we standardise the measure of openness/vulnerability, $s_{i,t} = \frac{\text{indicator}_{i,t} - \text{mean}(indicator)}{\sqrt{\text{var}(indicator)}}$, where the mean and variance of the indicator are computed for each country i along the time-series dimension; (ii) we take a logistic function of the standardised variable, $l_{i,t} = \frac{exp(s_{i,t})}{1+exp(s_{i,t})}$; (iii) we re-centre $l_{i,t}$ in terms of its 50-th and 95-th percentile, $l_{i,t}^{p} = \frac{l_{i,t}^{p} - l_i^{50}}{l_i^{95} - l_i^{50}}$; (iv) finally, we regress each characteristic $l_{i,t}^{p}$ on all the regressors of (3) and keep the residual $e_{i,t}^{v}$. The rationale be-

[12]The codebook of the database is available at: https://www.ecb.europa.eu/home/pdf/research/intlink/db/Code_Book_Intlink.pdf?76bbc1267568e3e3f6ae6643339a7696.

[13]For details on the construction of those two measures please refer to Iacoviello and Navarro (2018).

hind the above-mentioned steps is the following: the standardisation makes the various measures comparable, while the logistic transformation provides a probabilistic interpretation of the variable; the re-centering step allows us to interpret $\gamma_{i,h}$ and $\gamma_{i,h} + \gamma^v_{i,h}$ as the effects of the GFRUi when some characteristic (e.g. trade openness) is respectively at its median and at the 95th percentile of its distribution. Finally, the regression step is required to make $e^v_{i,t}$ orthogonal to the regressors in equation (3), thus ensuring that the coefficient estimates of (4) are going to be the same as those in the baseline, except for the interaction term, which can be interpreted as the marginal contribution of the characteristic under scrutiny.

3 Results

3.1 The Impact of Global Financial Risk and Uncertainty

Figure 4 presents the response of industrial production to the GFRUi shock using the model presented in (3). The average response to the shock is negative, persistent and statistically significant with 95% confidence for almost two years. A one-standard-deviation increase in the GFRUi leads to a 0.7 per cent decline in industrial production globally at its trough. In order to shed light on the global transmission of a shock to the GFRUi, we run separate regressions for advanced and emerging market economies. It is interesting to notice that while significant differences do not emerge from this exercise, the shock has a relatively smaller impact on emerging markets. In particular, industrial production in advanced economies falls by about 1% within the first 8 months, while in emerging economies it declines only by approximately 0.6%. To get a sense of the heterogeneity of the effects across the countries in our sample, we also estimate local projections using simple country-by-country regressions.[14] Figures 10 and 11 help us summarise the results and eyeball any potential geographical pattern relative to the magnitude and persistence of the output response to the shock. In particular, the two figures display maps of the world, in which the colour of each country depends on the size of the trough and median responses respectively. We see that for the majority of the countries in the sample the response to the shock is negative. Some countries like Japan, South Korea, Turkey, Romania, Estonia and Lithuania experience particularly strong declines in industrial production (between 1.5% and 2%). In Russia, the Scandinavian countries, most of western Europe and Brazil we find a decline of approximately 1%. Results are mixed for other countries in Asia and Oceania: while we find a persistent decline in IP for Malaysia, the responses in Thailand, the Philippines and Australia are either insignificant or mildly positive. All in all, no clear picture emerges from the analysis of country-by-country trough responses. More specifically, belonging to a particular geographic area does not appear to be a crucial determinant of the response to the shock. Also when analysing the median responses, it is not easy to identify any geographical pattern. For the majority of countries, the median response is negative, suggesting that the shock does not wind up quickly. However, for some countries, such as Mexico and Australia, the median response is positive, implying a lower persistence of the shock. The negative response to a GFRUi shock is in line with the findings in the existing literature on uncertainty shocks. In addition, the heterogeneity of the responses is a common feature of the studies on global spillovers of monetary policy shocks from a centre country (see Georgiadis, 2016 and Dedola et al., 2017).

[14]Figures 5 to 9 show the impulse response functions for all the countries in the sample to a one standard deviation increase in the GFRUi.

3.2 Transmission determinants

As discussed in the previous section, responses to a GFRUi shock are heterogeneous, yet we cannot easily identify a geographical pattern looking at the country-by-country responses. In this section, we shed light on the transmission determinants, by means of the regression model (4) described in section 2. Figures 12 and 13 show the results of this exercise. Specifically, the blue impulse response function represents the average effect as shown in the previous figures, while the red line can be interpreted as the response to the shock when one of the openness or vulnerability measures moves from its median to the 95th percentile.

Integration and openness Due to the global nature of the GFRUi, we decided to initially focus our attention on countries' openness to trade and particularly to global financial markets. The rationale is given by the fact that in the face of a global shock, countries with higher interlinkages might be more exposed to a global decline in activity.

Indeed, we find openness to trade and financial markets to be an important transmission mechanism that amplifies the effects of shocks to the GFRUi. Considering measures of *de facto* capital account openness, we find the responses under larger financial openness to be much more persistent than in the baseline case. After 20 months the IP response is three times as large than in the baseline scenario. Using the Chinn-Ito index of *de iure* capital account openness or the index on capital flows restrictions provided by Fernández et al. (2016), the effects are larger than in the baseline scenario, yet the difference is economically and statistically less significant. The results on trade, go in the same direction. Openness to trade implies a response that is more than twice larger than in the baseline scenario. The significance of these estimates varies with the indicator chosen.

Vulnerabilities The second group of characteristics which we take into account relates to countries' vulnerabilities. In order to capture potential vulnerabilities, we consider two measures of country risk rating, namely composite and financial risk rating,[15] and a measure of government stability. Additionally, we consider three measures related to debt levels, the current account balance and two different measures assessing the depth of financial markets. We find that countries with a higher financial risk rating and with larger debt denominated in a foreign currency are hit by the shock more severely (approximately twice as much than the baseline case). Furthermore, as shown in figure 21, we find that having a currency pegged to the dollar does not significantly affect the transmission of global uncertainty shocks. This result is interesting, as it sheds light on a potential transmission mechanism of global risk and uncertainty shocks. Specifically, in the face of a rise in global uncertainty, a safe haven currency such as the U.S. dollar is expected to appreciate. When countries peg to the dollar, their possibility to resort to monetary policy to counteract the shock is curtailed. Thus, we would expect countries pegging their currency to experience a larger negative response to the shock. A possible explanation for our findings is that monetary authorities in the U.S. respond to an increase in global risk and uncertainty by loosening monetary policy, thus partly or entirely offsetting the appreciation pressures. The literature on spillovers from U.S. monetary policy shocks finds instead that pegging to the U.S. dollar is a source of amplification of the original shock (see for example Iacoviello and Navarro (2018)). In line with the results discussed above, we find that countries with high financial vulnerability, as measured by the vulnerability index constructed by Iacoviello and Navarro (2018), suffer a stronger fall in IP (almost twice as large as in the baseline case). This latter result is strongly statistically significant and particularly interesting as it underlines that vulnerabilities matter perhaps not only in isolation and that their combination is potentially

[15] Notice that the financial risk rating index is also used for the computation of the composite risk rating index, which also includes a measure of economic and political risk.

more relevant for the transmission of the shock by rendering countries more prone to suffer the negative consequences of global shocks.

3.3 Robustness

In this subsection, we discuss various alternatives to the main empirical exercises to test the robustness of our results.

External Instrument Identification. We consider an identification strategy alternative to the recursive identification described in 2.2.1. In particular, we run the alternative panel regression:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \gamma_{i,h}\mathrm{GFRUi}_t + +B_{i,h}^{Global}(L)\,X_{i,t}^{Global} + B_{i,h}^{Local}(L)\,X_{i,t-1}^{Local} + \varepsilon_{i,t+h}. \quad (5)$$

This regression model is the same as in equation (3), except for not including lags of the $GFRUi$. In order for the parameter $\gamma_{i,h}$ to be interpreted structurally, we estimate the model by instrumental variable estimation. The external instrument is given by the variations in the price of gold around events associated with unexpected changes in uncertainty, which is taken from Piffer and Podstawski (2018). More specifically, the events of heightened uncertainty include the dates identified in Bloom (2009) as well as a list of other armed conflicts, terrorist attacks, political elections and judicial decisions.

The instrument is constructed using intradaily data on the London spot market of physical gold, employing prices from the two daily auctions at 10:30 and 15:00. The proxy for the uncertainty shock is computed as the percentage change of the price of gold around the selected events. The monthly time series is obtained summing up the daily proxy within a month, similarly as in Romer and Romer (2004). The *exogeneity* of the instrument is discussed in detail in Piffer and Podstawski (2018), who regress (in separate regressions) the instrument on a variety of shocks previously identified in the literature, such as oil price shocks, monetary policy shocks, fiscal policy shocks and productivity shocks and show that parameter estimates are not significantly different from zero. This test indicates that the instrument is not mistakenly picking up the other sources of shocks. The second condition an instrument needs to satisfy is *relevance*. In other words, the instrument needs to be significantly correlated with the endogenous variable. The correlation of the instrument with the GFRUi is approximately 21%. We test the statistical relevance of the instrument by regressing the GFRUi on the instrument and a constant. In the first-stage regression, the instrument's coefficient estimate is 19.86 and significantly different from 0 with a 90% confidence. We conclude that the instrument is relevant. Figure 15 displays the responses to a 1 standard deviation shock using the alternative identification strategy. The decline in IP is in line and slightly more pronounced than in the baseline case, presented in figure 4. Specifically, advanced economies suffer approximately a 2.5% fall in IP while industrial production in EMEs declines by approximately 1.5%.

Additional controls and lags. We include oil prices as an additional control in model (3), contemporaneously determined to the GFRUi, which is equivalent to placing the GFRUi below oil prices in a Cholesky identification. The rationale behind this exercise is to avoid the potential confounding of financial uncertainty and oil price shocks. Furthermore, we include a measure of Euro Area (EA) short-term interest rates in model (3). We do so to control for the contemporaneous effects of ECB's monetary policy on the GFRUi. In particular, we construct a measure of EA interest rate from 1991, by extracting the first principal component from the short-term interest rates of the main Euro Area economies (Germany, France, Italy and Spain) and the EONIA rate, available only from 1999 onwards [16]. Finally, we consider how increasing to 6 the number of lags in regression 3 affects our results.[17] Since local projections do not impose any dynamic restrictions on the IRFs, we do not expect these changes to have major effects. Figures 16 to 17 display the results from the robustness exercises. The profile of the IRFs is substantially unaffected by the various robustness exercises conducted.

The Global Financial cycle index Figures 18 to 20 replicate our empirical exercise for a different but strictly related measure to the GFRUi which we label the *Global Financial Cycle index* (GFCi), described in subsection 2.2.1 and in more detail in the appendix D. The main difference with the GFRUi is that the GFCi is not derived from the second moment of the data series, therefore it is similar to a financial condition index, rather than a global uncertainty measure. The results from this shock are similar to those presented above. A tightening in global financial conditions strongly affect industrial production in both advanced and emerging market economies. Also for this shock, higher vulnerability and higher openness amplify the initial shock.

4 Conclusion

In this paper, we investigate how an unexpected rise in global financial uncertainty affects economic activity, using a panel of 44 small open economies. To this end, we first extract a global factor of the realised volatility of nearly 1000 financial risky asset returns and argue this factor to be mainly driven by fluctuations in uncertainty and risk aversion. We then identify shocks

[16]Missing observations are imputed using an expectation maximisation algorithm
[17]We also explored alternative lag structures which are not presented here for the sake of brevity.

to this factor and study its impact on economic activity by estimating local projections based on a panel regression model with country fixed effects. To this end, we consider a panel of 44 economies, spanning from 1991M1 until 2016M12. We find that shocks increasing the GFRUi dampen strongly and persistently economic activity in the vast majority of the countries in our panel. While we document that the effects are rather heterogeneous and without clear geographical patterns, we identify several factors that make countries more sensitive to increases in the GFRUi. In particular, we show that countries with larger vulnerabilities (such as high level of debt), as well as countries with a high degree of financial and trade openness, tend to be more affected by an increase in global financial uncertainty. This evidence can shed light on the international transmission of uncertainty shocks, pointing to the importance of both trade and financial channels. From a policy perspective, these results may suggest that policymakers face a trade-off between isolating their country from global shocks and pursuing long-run growth. Therefore, a policy question related to this study is how policymakers should reconcile the deepening of global integration while ensuring that their countries are resilient to adverse global shocks.

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A Tables

Table 1: Financial series included in the estimation of the GFRUi

Region:	*America*	*United States*	*Europe*	*Asia*	*Commodities*	*Banks*	*Oceania*
Series:	164	162	158	139	40	73	69

Note: The table reports the number of series used to compute the GFRUi grouped by geographical area. The series represent equity market indices and are all provided by Thomson Reuters/Datastream. The numbers consider only series for which observations are continuously available from December 1989 onwards. America includes north centre and south America stock market series.

Table 2: Summary statistics for the exposure measures

Country	Income level	De-facto financial openness	De-iure financial openness	Capital flows restrictions	Trade openness	Comp. country risk rating	Financial risk rating	Govt. stability	Public Debt to GDP	Debt in foreign currency	Debt sustainability	Current Account balance	Overall financial development	Financial development
Australia	1	56%	50%	56%	13%	69%	27%	84%	13%	4%	56%	7%	91%	69%
Austria	1	73%	75%	29%	67%	82%	76%	71%	82%	48%	27%	71%	64%	62%
Belgium	1	87%	73%	2%	98%	71%	69%	56%	91%	-	24%	64%	62%	42%
Brazil	0	13%	9%	73%	2%	13%	18%	16%	76%	43%	38%	9%	51%	38%
Bulgaria	0	44%	36%	51%	71%	18%	9%	4%	27%	96%	78%	47%	11%	29%
Canada	1	58%	89%	34%	53%	78%	78%	78%	89%	-	40%	18%	89%	89%
Chile	0	53%	32%	71%	42%	58%	58%	67%	7%	-	89%	44%	38%	51%
China	0	16%	2%	98%	29%	40%	89%	96%	24%	-	82%	96%	40%	78%
Colombia	0	7%	11%	90%	9%	7%	40%	42%	36%	74%	76%	33%	9%	18%
Czech Republic	1	40%	52%	46%	87%	53%	53%	9%	22%	-	33%	36%	24%	31%
Denmark	1	71%	86%	34%	51%	91%	87%	51%	58%	-	62%	76%	71%	84%
Estonia	1	60%	84%	-	93%	33%	4%	82%	2%	-	91%	53%	18%	40%
Finland	1	84%	75%	49%	44%	84%	44%	80%	51%	-	60%	69%	53%	49%
France	1	82%	68%	15%	27%	62%	60%	49%	78%	35%	13%	58%	67%	58%
Germany	1	67%	89%	24%	47%	76%	84%	73%	73%	-	31%	93%	76%	67%
Greece	1	64%	48%	22%	11%	24%	7%	18%	96%	-	2%	20%	47%	44%
Hungary	0	76%	41%	54%	89%	36%	16%	20%	80%	78%	20%	40%	36%	24%
India	0	2%	5%	95%	7%	11%	62%	11%	84%	-	7%	13%	27%	22%
Indonesia	0	9%	45%	85%	31%	4%	38%	24%	38%	83%	80%	38%	13%	20%
Ireland	1	96%	64%	32%	76%	73%	49%	76%	67%	4%	44%	60%	87%	60%
Italy	1	51%	68%	2%	22%	51%	51%	2%	93%	26%	11%	29%	73%	47%
Japan	1	38%	82%	10%	4%	80%	93%	44%	98%	-	4%	98%	78%	98%
Latvia	1	49%	80%	39%	69%	29%	11%	69%	9%	61%	67%	51%	7%	33%
Lithuania	1	27%	57%	-	80%	38%	22%	53%	20%	91%	53%	49%	4%	11%
Luxembourg	1	98%	-	-	73%	96%	91%	98%	4%	13%	84%	67%	80%	56%
Malaysia	0	47%	30%	93%	96%	60%	80%	89%	49%	-	58%	78%	56%	82%
Mexico	0	20%	39%	76%	38%	31%	56%	29%	44%	65%	69%	16%	20%	2%
Netherlands	1	93%	89%	2%	82%	89%	71%	58%	69%	39%	36%	87%	84%	73%
Norway	1	69%	55%	20%	36%	98%	96%	33%	29%	-	98%	84%	60%	64%
Philippines	0	24%	20%	88%	64%	20%	36%	22%	62%	-	73%	62%	22%	16%
Poland	0	22%	16%	80%	56%	47%	31%	7%	53%	-	29%	22%	31%	13%
Portugal	1	80%	61%	44%	40%	56%	29%	47%	87%	57%	9%	24%	58%	76%
Romania	0	11%	34%	61%	58%	9%	13%	13%	18%	87%	93%	31%	2%	4%
Russia	0	18%	23%	83%	18%	16%	47%	91%	16%	-	96%	91%	29%	7%
Slovakia	1	31%	27%	-	91%	42%	24%	36%	40%	52%	22%	42%	16%	27%
Slovenia	1	42%	43%	68%	84%	44%	20%	87%	31%	-	47%	56%	42%	36%
South Africa	0	36%	7%	66%	33%	22%	33%	64%	33%	-	51%	27%	44%	91%
South Korea	1	29%	25%	59%	60%	64%	82%	27%	11%	22%	87%	82%	82%	71%
Spain	1	62%	59%	17%	24%	49%	42%	40%	71%	30%	18%	4%	93%	80%
Sweden	1	78%	66%	27%	49%	87%	64%	31%	60%	70%	49%	80%	69%	53%
Switzerland	1	91%	89%	39%	62%	93%	98%	93%	56%	-	42%	89%	98%	96%
Thailand	0	33%	18%	78%	78%	27%	73%	38%	42%	-	64%	73%	49%	87%
Turkey	0	4%	14%	63%	16%	2%	2%	60%	47%	-	71%	11%	33%	9%
United Kingdom	1	89%	89%	12%	20%	67%	67%	62%	64%	17%	16%	2%	96%	93%

Note: The table reports the percentile rank of the average openness and vulnerability measures over the period $1991-2016$. *Income level* $=1$ *for advanced economies,* $=0$ *for emerging markets.*

Table 3: Data sources and availability

Country	Industrial production		CPI Inflation		Short-term rate		
	sample	**source**	**sample**	**source**	**sample**	**source**	**definition**
Australia	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money market rate
Austria	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Interbank Rate (3 month)
Belgium	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate (13 weeks)
Brazil	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Bulgaria	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	02/2003-12/2016	IMF(IFS)	Sofibor 3 month
Canada	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate
Chile	01/1991-12/2016	Haver	01/1991-12/2016	OECD (MEI)	01/1991-12/2016	IMF(IFS)	Lending Rate
China	01/1991-12/2016	CPB	01/1993-12/2016	OECD (MEI)	01/1991-12/2016	OECD (MEI)	Call Money Rate
Colombia	01/1991-12/2016	Haver	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Discount Rate
Czech Republic	01/1991-12/2016	CPB	12/1992-12/2016	IMF(IFS)	01/1993-12/2016	IMF(IFS)	Money Market Rate
Denmark	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Interbank Rate (3 month)
Estonia	01/1991-12/2016	CPB	01/1992-12/2016	IMF(IFS)	02/1993-12/2016	IMF(IFS)	Deposit Rate
Finland	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Avg Cost of CB Debt
France	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate (3 months)
Germany	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Interbank Rate (3 month)
Greece	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate (3 months)
Hungary	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Deposit Rate
India	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Call Money Rate
Indonesia	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/2005-12/2016	IMF(IFS)	JIBOR 3 month
Ireland	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	Haver	Interbank Rate (3 month)
Italy	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate
Japan	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Call Money Rate
Latvia	01/1991-12/2016	CPB	01/1992-12/2016	IMF(IFS)	08/1993-12/2016	IMF(IFS)	Money Market Rate
Lithuania	01/1991-12/2016	CPB	05/1992-12/2016	IMF(IFS)	12/1993-12/2016	IMF(IFS)	Money Market Rate
Luxembourg	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1999-12/2016	IMF(IFS)	Money Market Rate
Malaysia	01/1991-12/2016	Haver	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Mexico	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Avg Cost of Funds
Netherlands	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Deposit Rate
Norway	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	OECD (MEI)	Interbank Rate (3 month)
Philippines	01/1991-12/2016	Datastream	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Lending Rate
Poland	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Portugal	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Interbank Rate (3 month)
Romania	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/2003-12/2016	Haver	Official interest rate
Russia	01/1991-12/2016	CPB	01/1992-12/2016	IMF(IFS)	01/1995-12/2016	IMF(IFS)	Money Market Rate
Slovakia	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1995-12/2016	IMF(IFS)	Money Market Rate
Slovenia	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/2002-12/2016	IMF(IFS)	Money Market Rate
South Africa	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
South Korea	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Spain	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Sweden	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Call Money Rate
Switzerland	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	Haver	Call Money Rate
Thailand	06/1998-12/2016	Datastream	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Money Market Rate
Turkey	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	Deposit Rate
United Kingdom	01/1991-12/2016	CPB	01/1991-12/2016	IMF(IFS)	01/1991-12/2016	IMF(IFS)	T-bill Rate (3 months)

Notes: The table provides information on the data sources and availability.

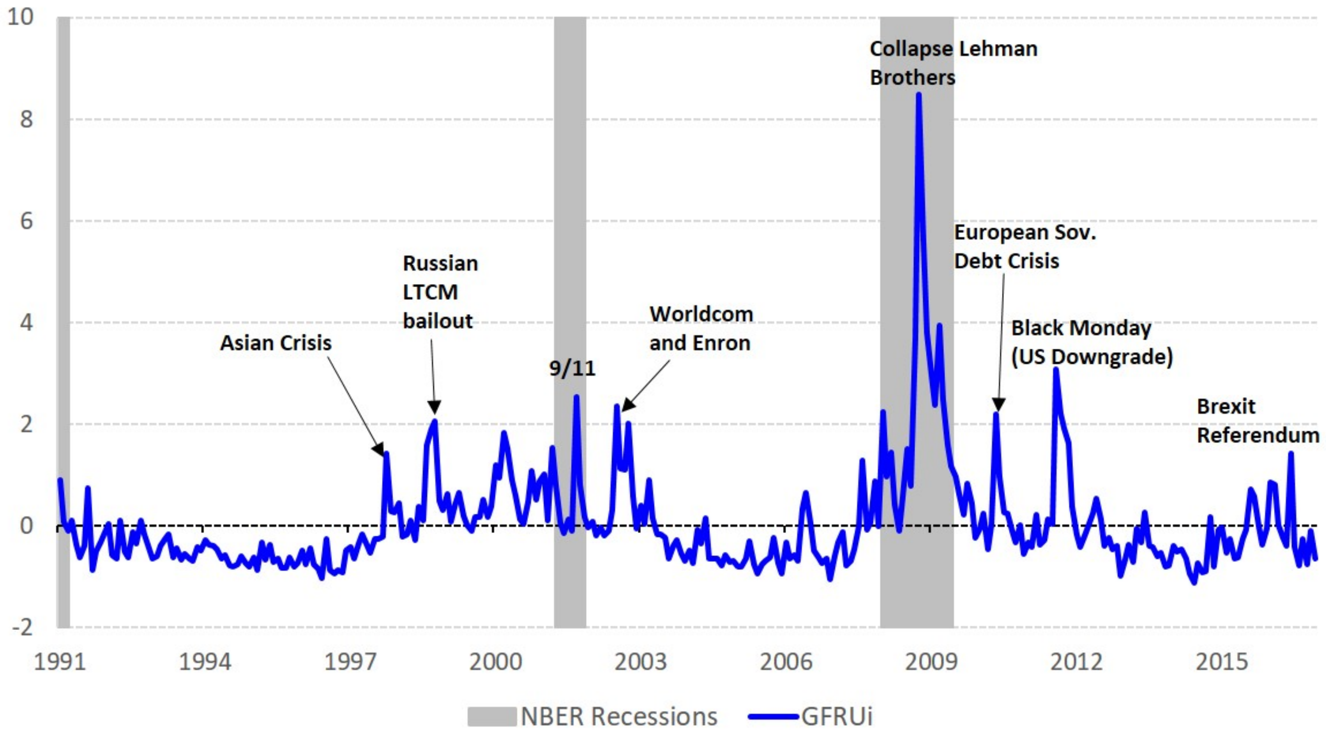
Table 4: Transmission determinants of exposure to GFRUi shock

Group	**Country characteristic**	**Measurement\Source**
Openness/integraton	De-facto financial openness	Foreign assets plus liabilities relative to GDP
	De-iure financial openness (Chinn-Ito)	Chinn and Ito (2003) - IMF
	Capital flows restrictions	Fernandez, Klein, Rebucci, Schindler and Uribe (2016)
	Trade openness (exports+imports over GDP)	Export plus imports realtive to GDP
Vulnerabilities	Composite country risk rating	PRS - ICRG
	Financial risk rating	PRS - ICRG
	Government stabillity	PRS - ICRG
	Public Debt to GDP	General government gross debt relative to GDP - IMF WEO
	Debt in foreign currency	General government debt in foreign currency (% total) - World Bank
	Debt sustainability	Sustainability gap, fiscal balance relative to GDP - World Bank
	Current Account balance	IMF - IFS
	Overall financial development	Overall index of financial development - IMF
	Financial development	Domestic credit to private sector relative to GDP

Notes: The table provides information on the measurement and the data sources of the exposure characteristics considered. PRS-ICRG is the international country Risk Guide of the PRS Group. IMF IFS refers to International Monetary Fund International Financial Statistics. IMF WEO refers to International Monetary Fund World Economic Outlook database.

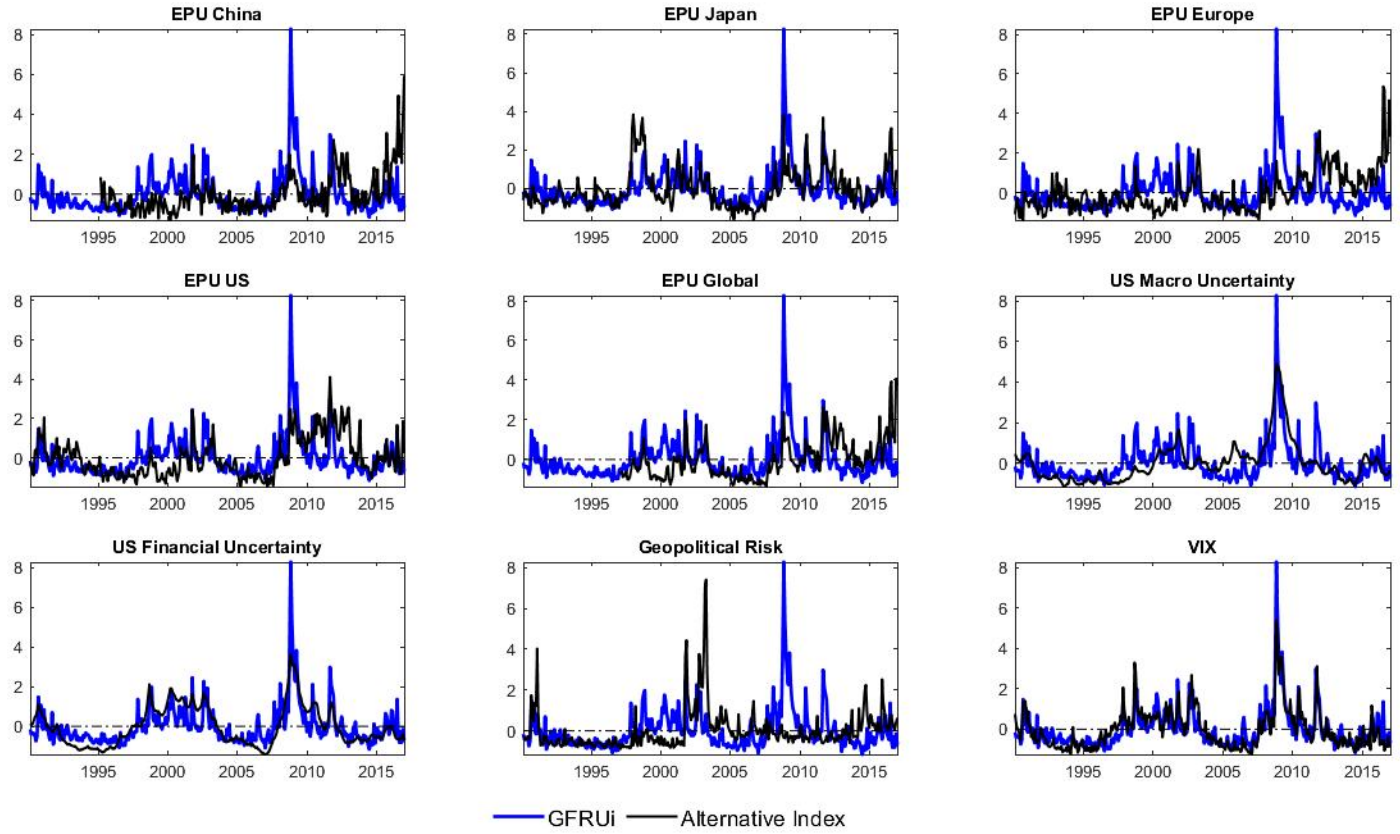
B Figures

Figure 1: The Global Financial Risk and Uncertainty Index



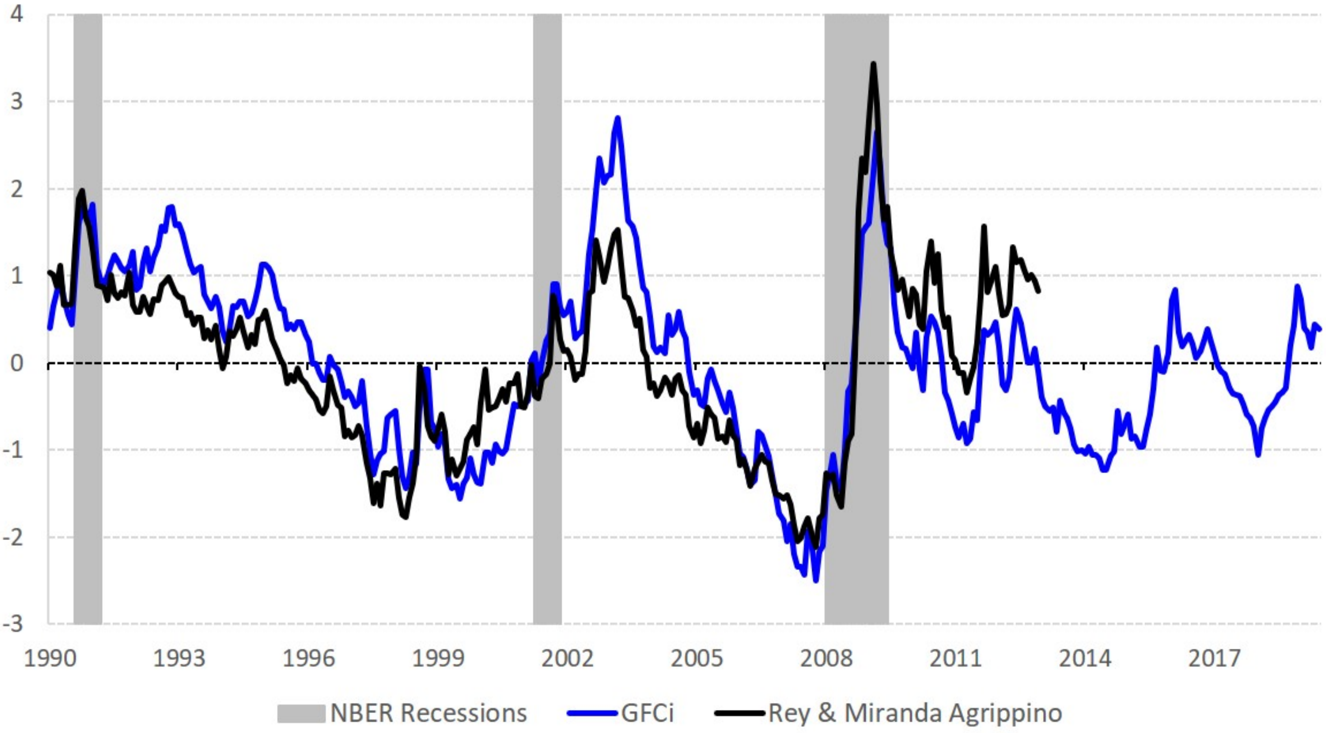
Note: The Global Financial Risk and Uncertainty Index plotted vis-à-vis some important political and economic events from January 1990 to July 2019. Shaded areas represent NBER recessions for the U.S.

Figure 2: GFRUi and other uncertainty indexes



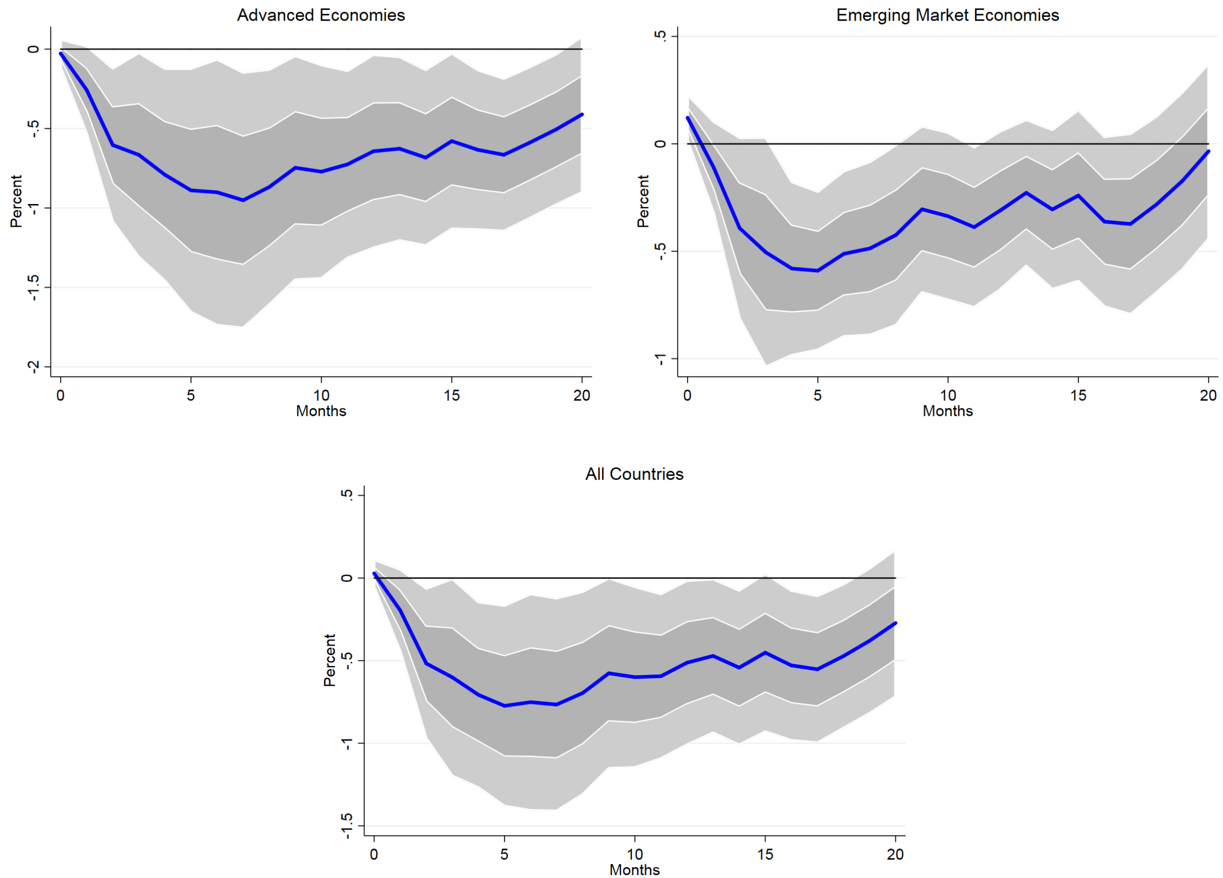
Note: The figure displays the GFRUi and selected indexes of volatility and uncertainty. All indexes have been standardised to facilitate the comparison. The correlation between the GFRUi and the other indexes are as follows: EPU China 0.5%, EPU Japan 50.5%, EPU Europe 11.0%, EPU US 42.0%, EPU Global 14.4%, Macro Uncertainty 67.4%, Financial Uncertainty 76.3%, Geopolitical Risk 3.0%, VIX 85.0%.

Figure 3: Global Financial Cycle Index



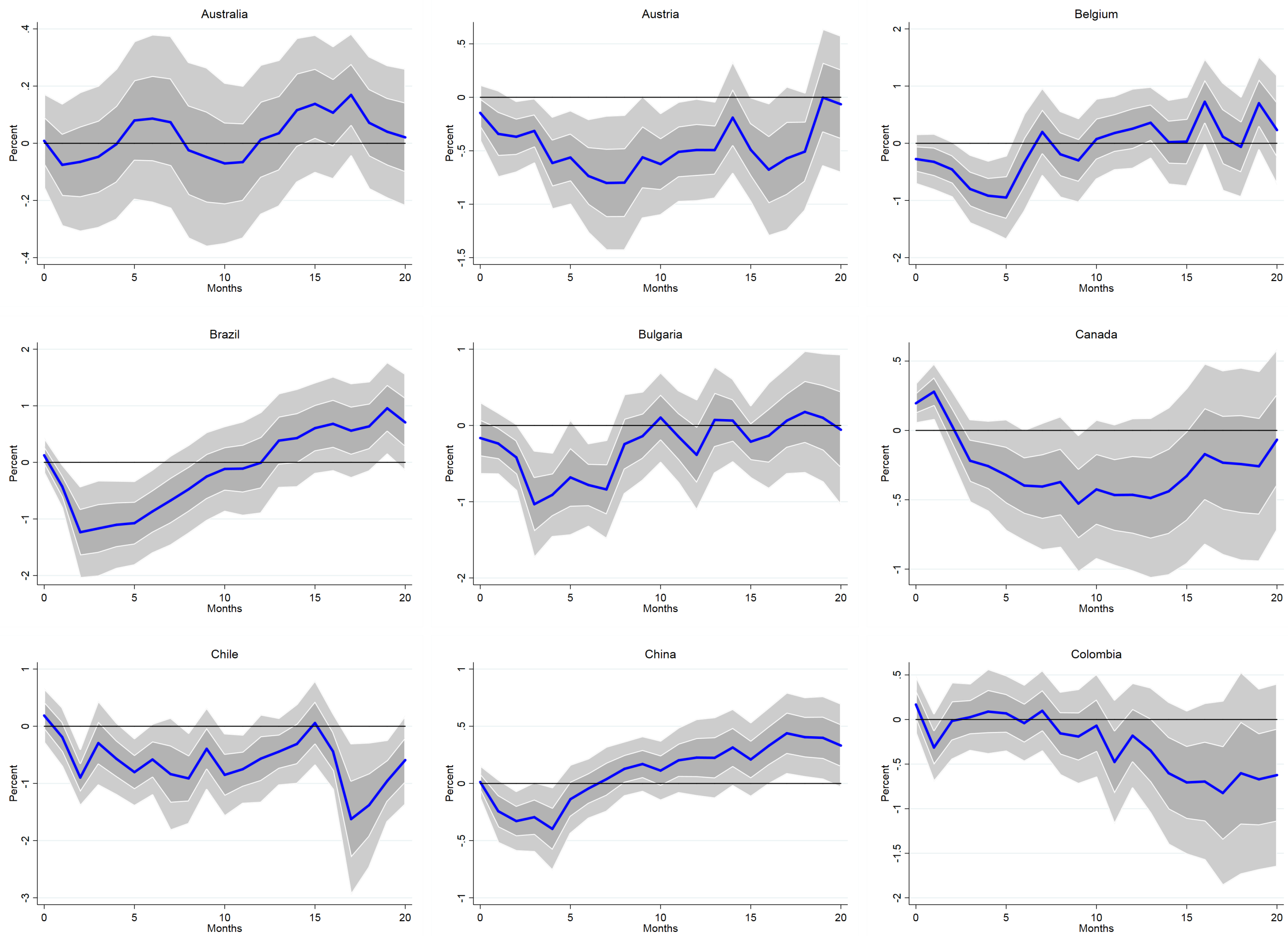
Note: The Global Financial cycle index constructed as the principal component of a large number of risky assets' prices.

Figure 4: Effect of GFRUi on industrial production



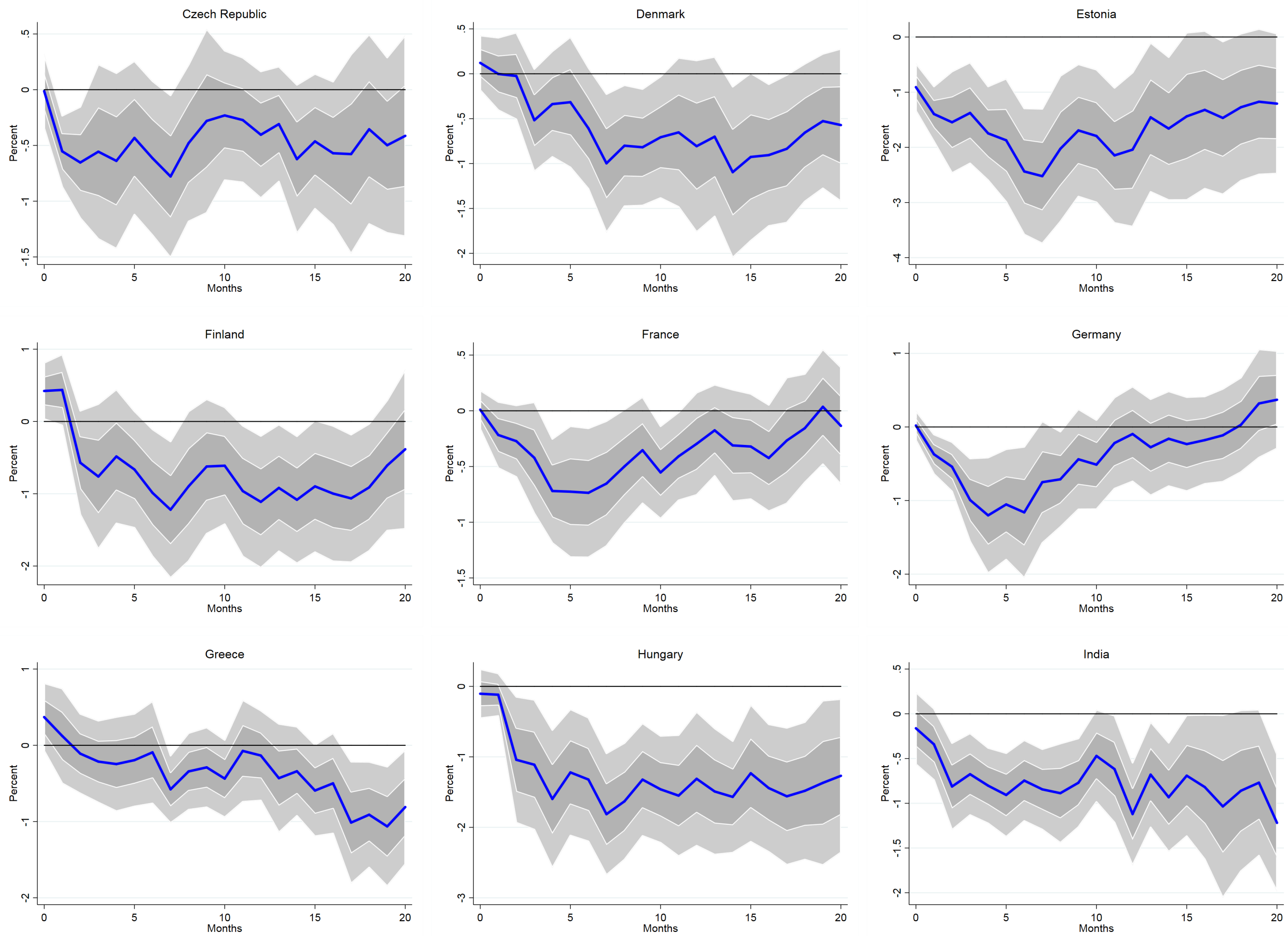
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence interval computed using Driscoll and Kraay (1995) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 5: Effect of GFRUi on countries' industrial production



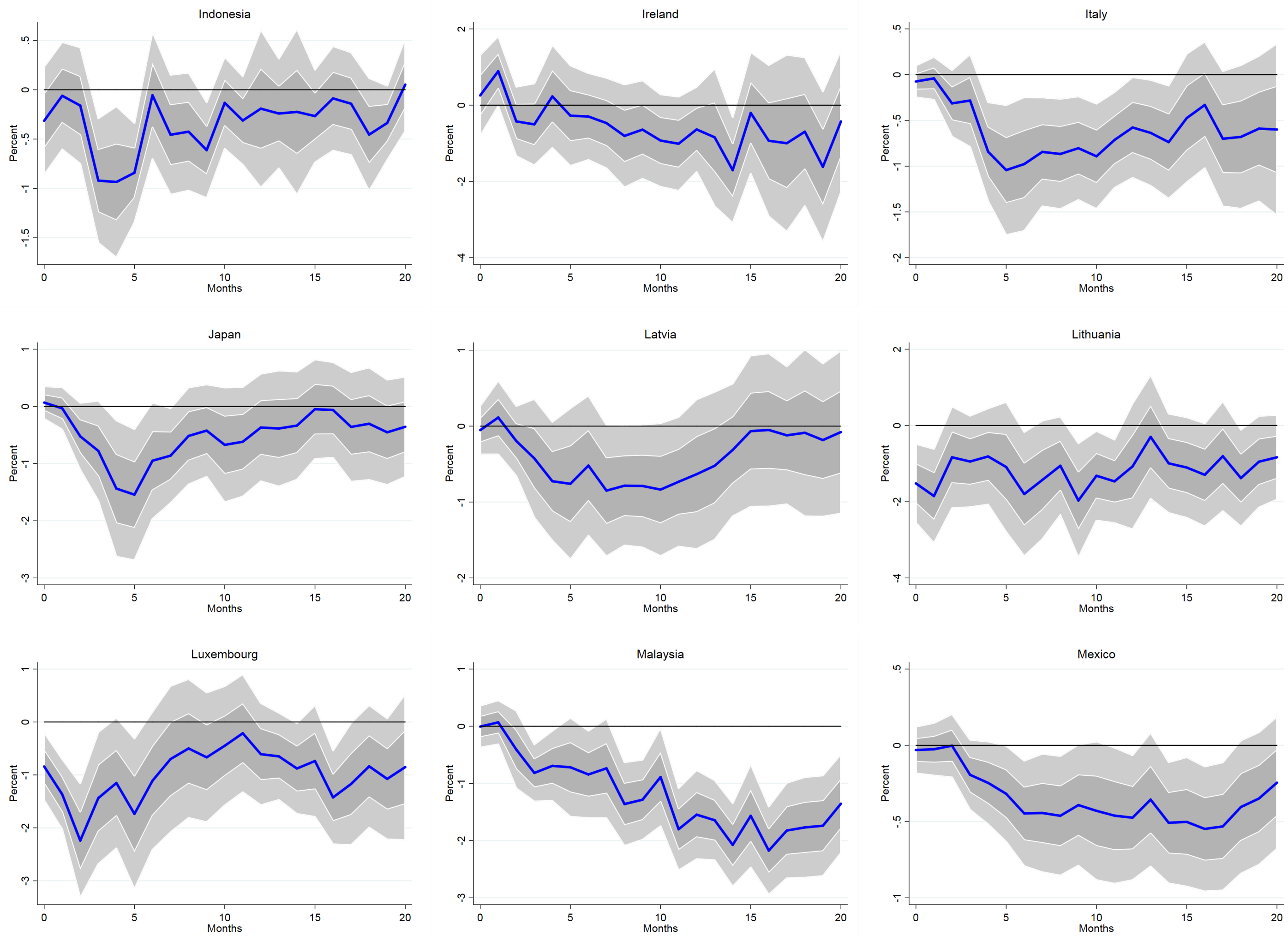
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence interval, computed using Newey-West HAC standard errors.

Figure 6: Effect of GFRUi on countries' industrial production



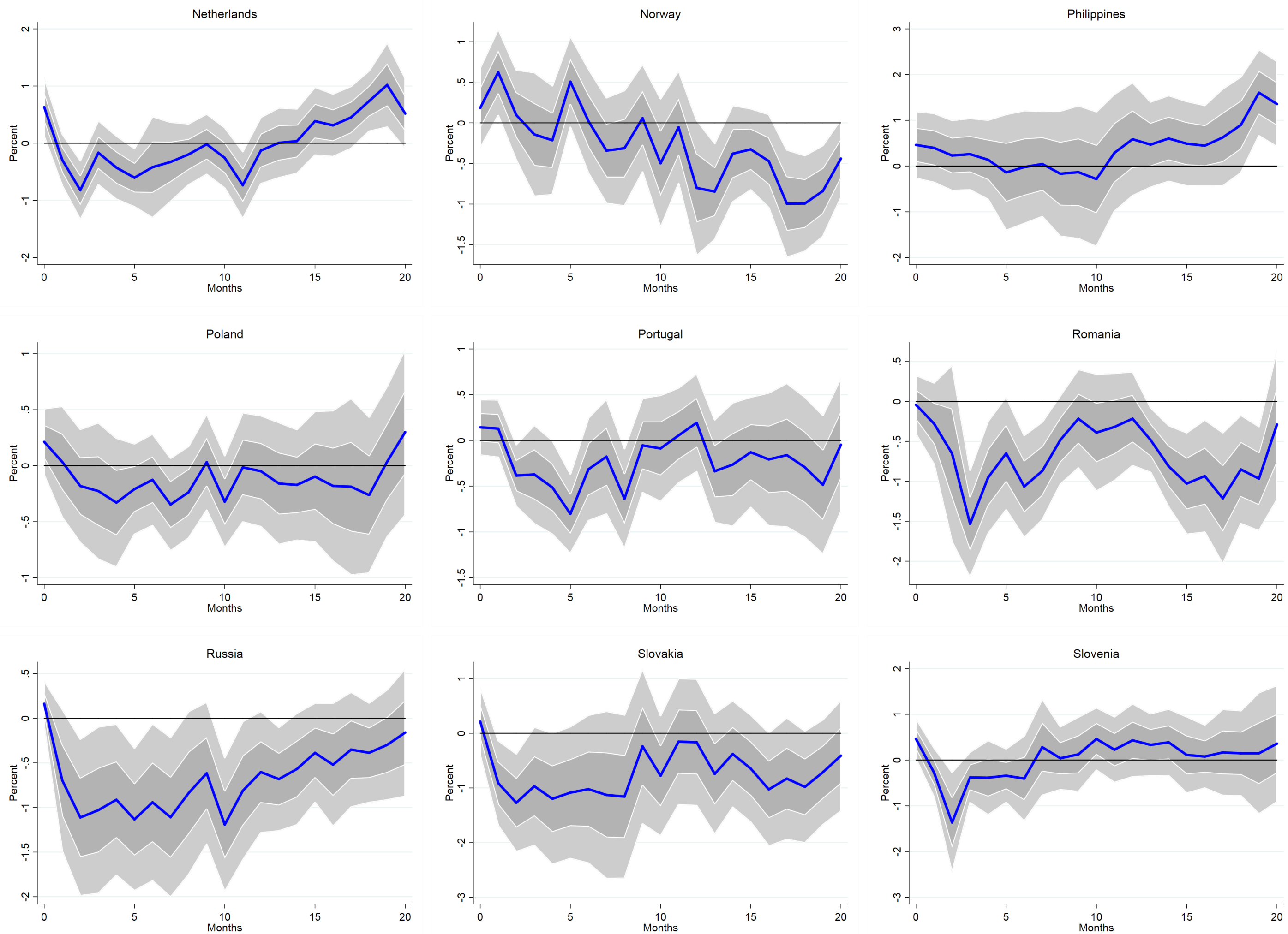
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence intervals, computed using Newey-West HAC standard errors.

Figure 7: Effect of GFRUi on countries' industrial production



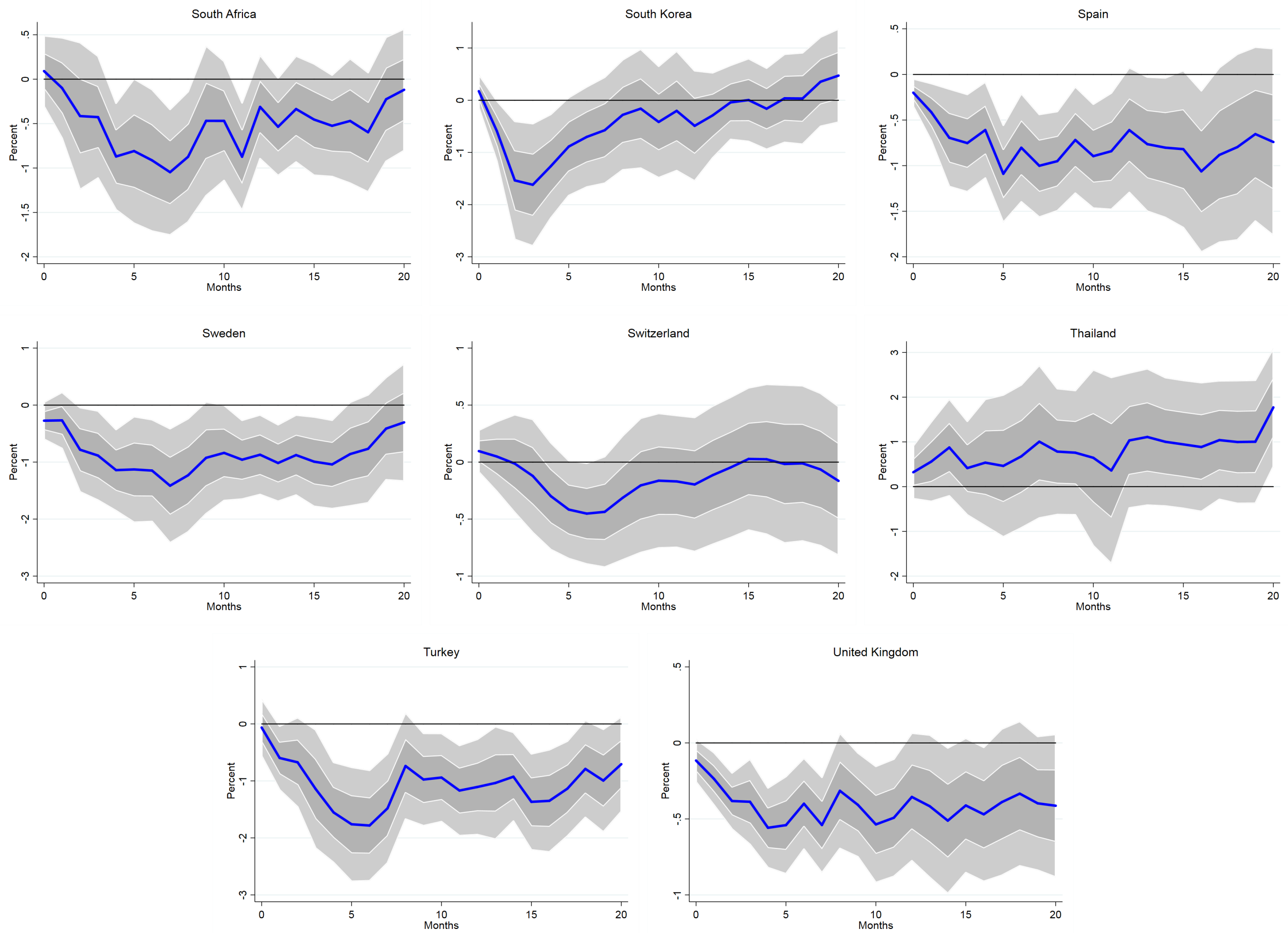
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence intervals, computed using Newey-West HAC standard errors.

Figure 8: Effect of GFRUi on countries' industrial production



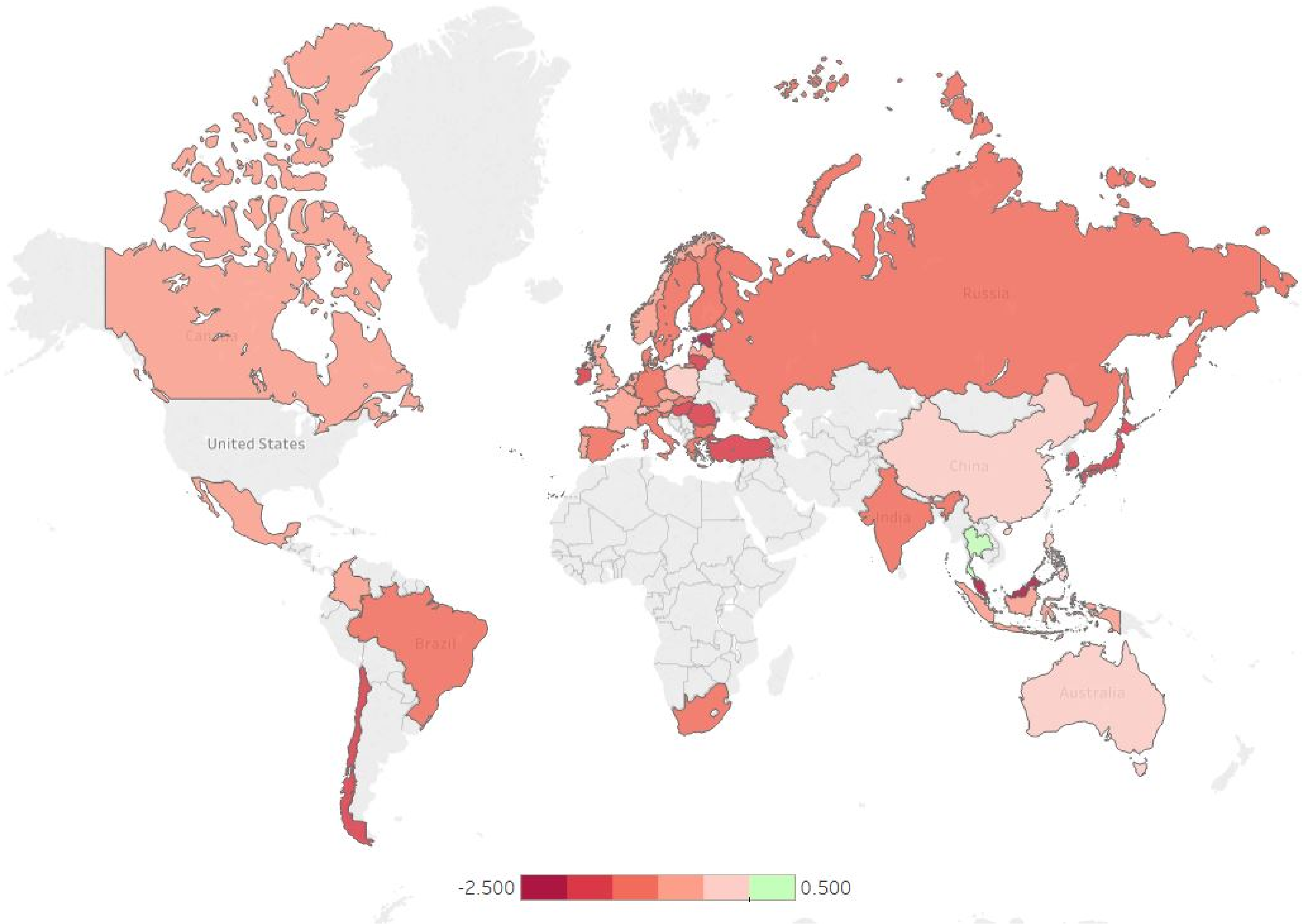
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence intervals, computed using Newey-West HAC standard errors.

Figure 9: Effect of GFRUi on countries' industrial production



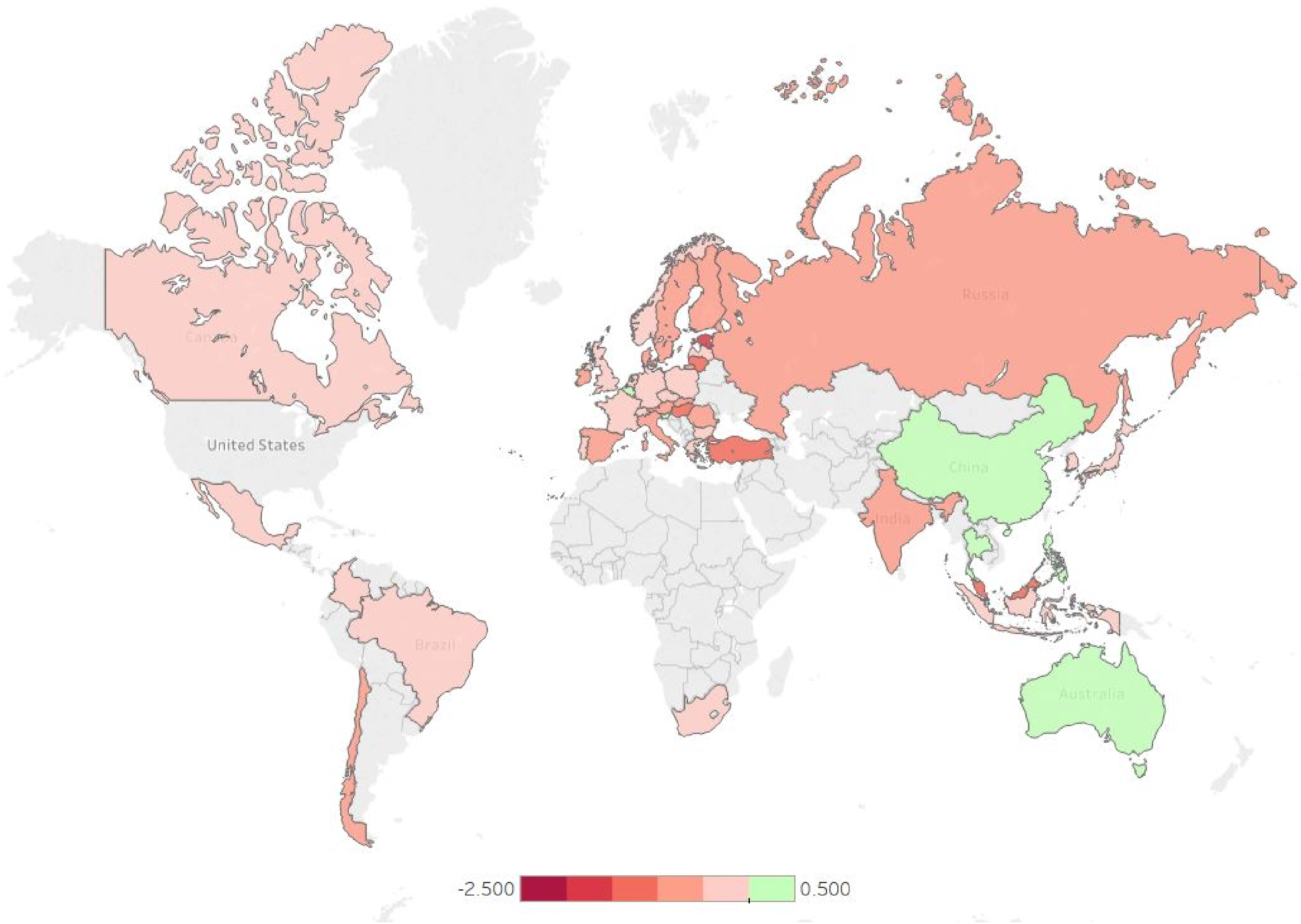
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence intervals, computed using Newey-West HAC standard errors.

Figure 10: *Effect of GFRUi on countries' industrial production: trough response*



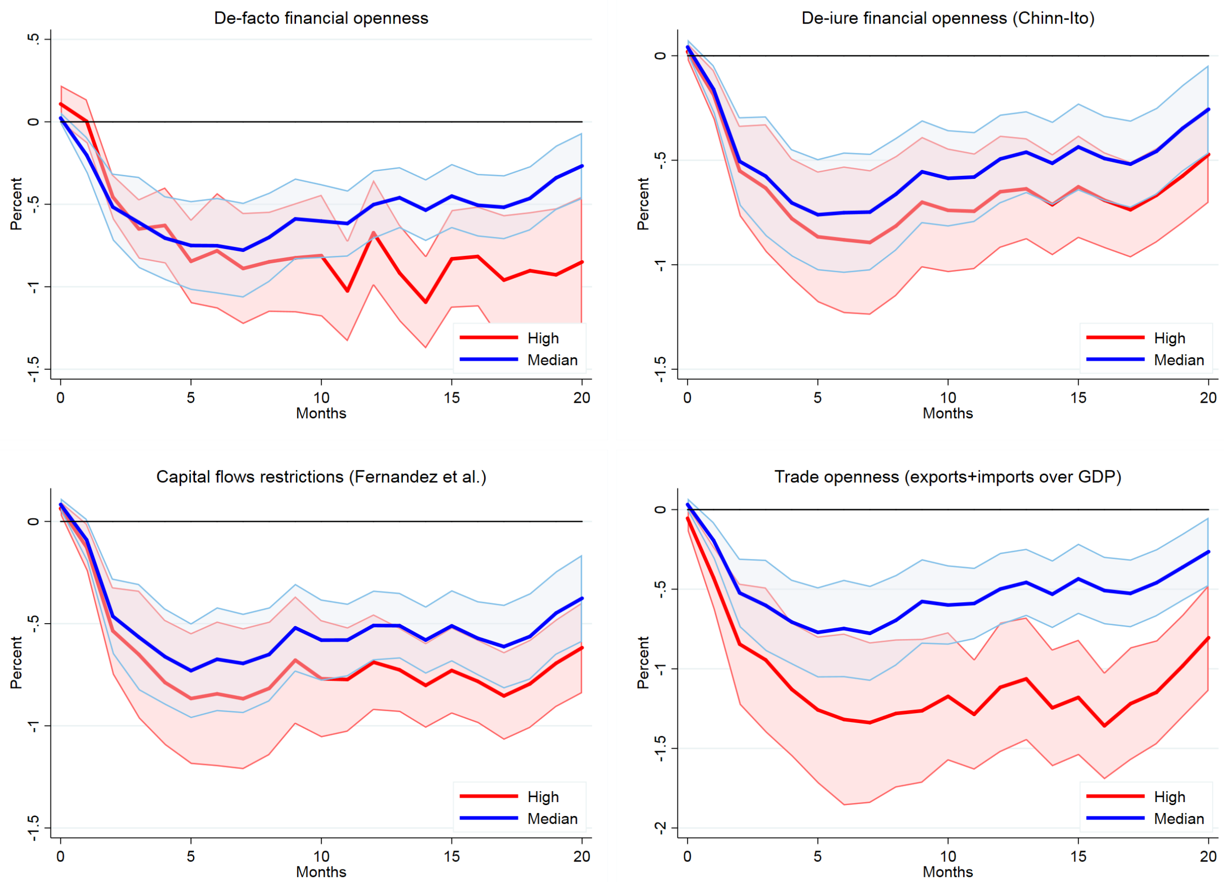
Note: The figure shows the trough response in industrial production for the countries in the sample for a 1 standard deviation shock in the GFRUi.

Figure 11: Effect of GFRUi on countries' industrial production: median response



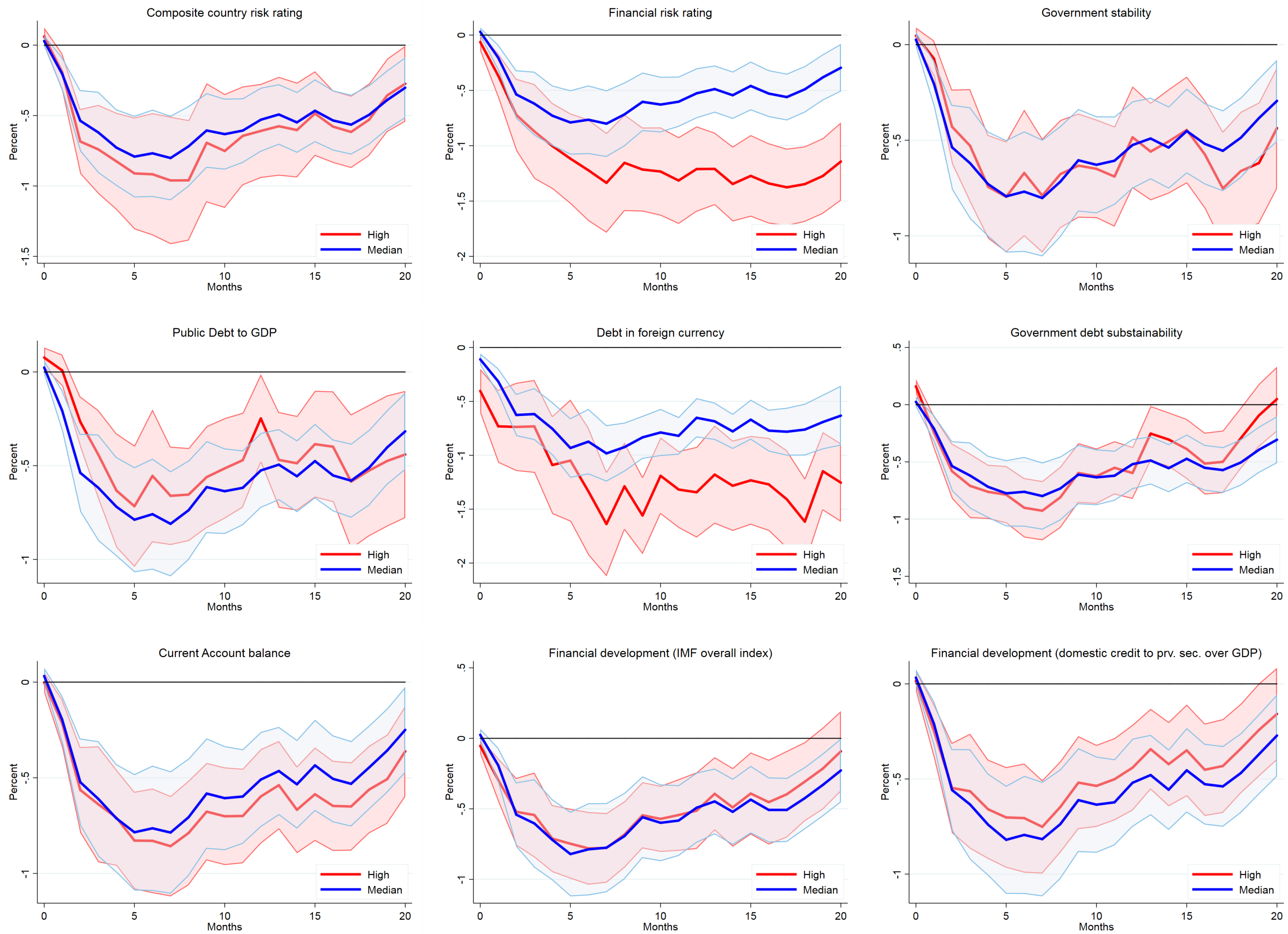
Note: The figure shows the median response in industrial production for the countries in the sample for a 1 standard deviation shock in the GFRUi.

Figure 12: Effect of GFRUi on countries' industrial production: integration and openness



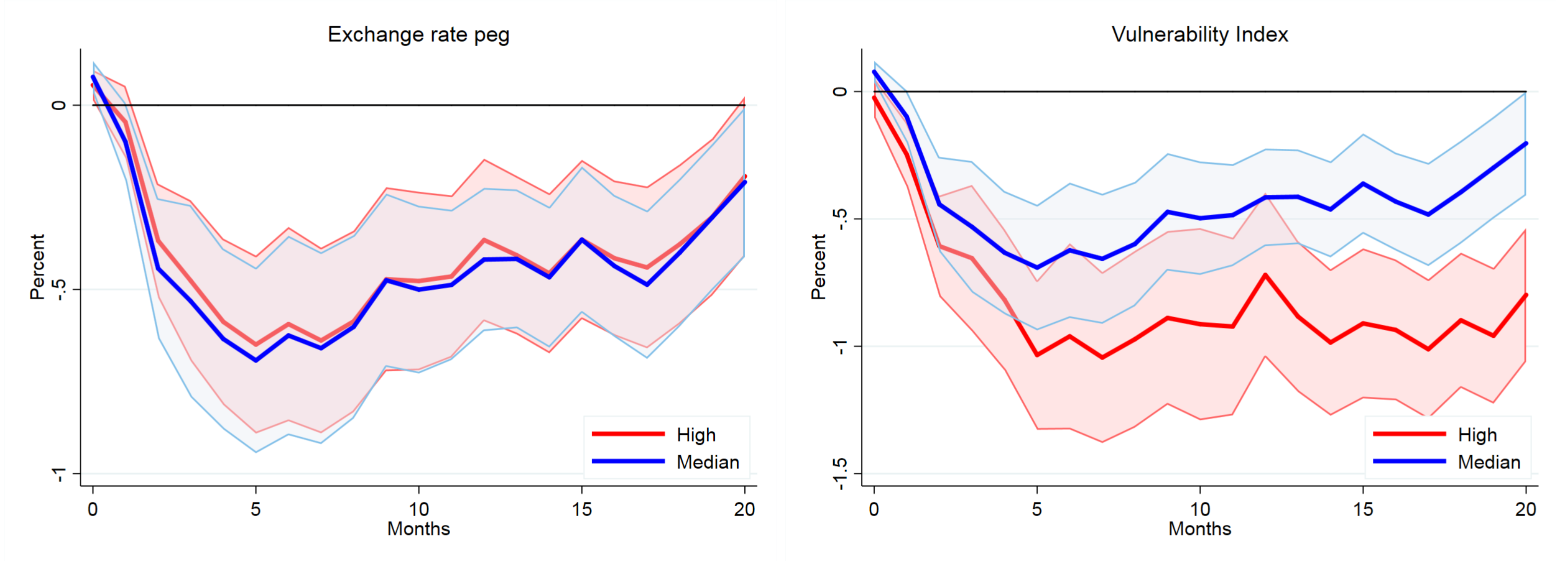
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval. For de-facto financial openness we excluded Luxembourg and Ireland from the sample due to the extraordinary high level of the index for both countries. Results are still robust to the inclusion of those countries. High in the case of capital flows restrictions means a more open capital account.

Figure 13: Effect of GFRUi on countries' industrial production: vulnerabilities



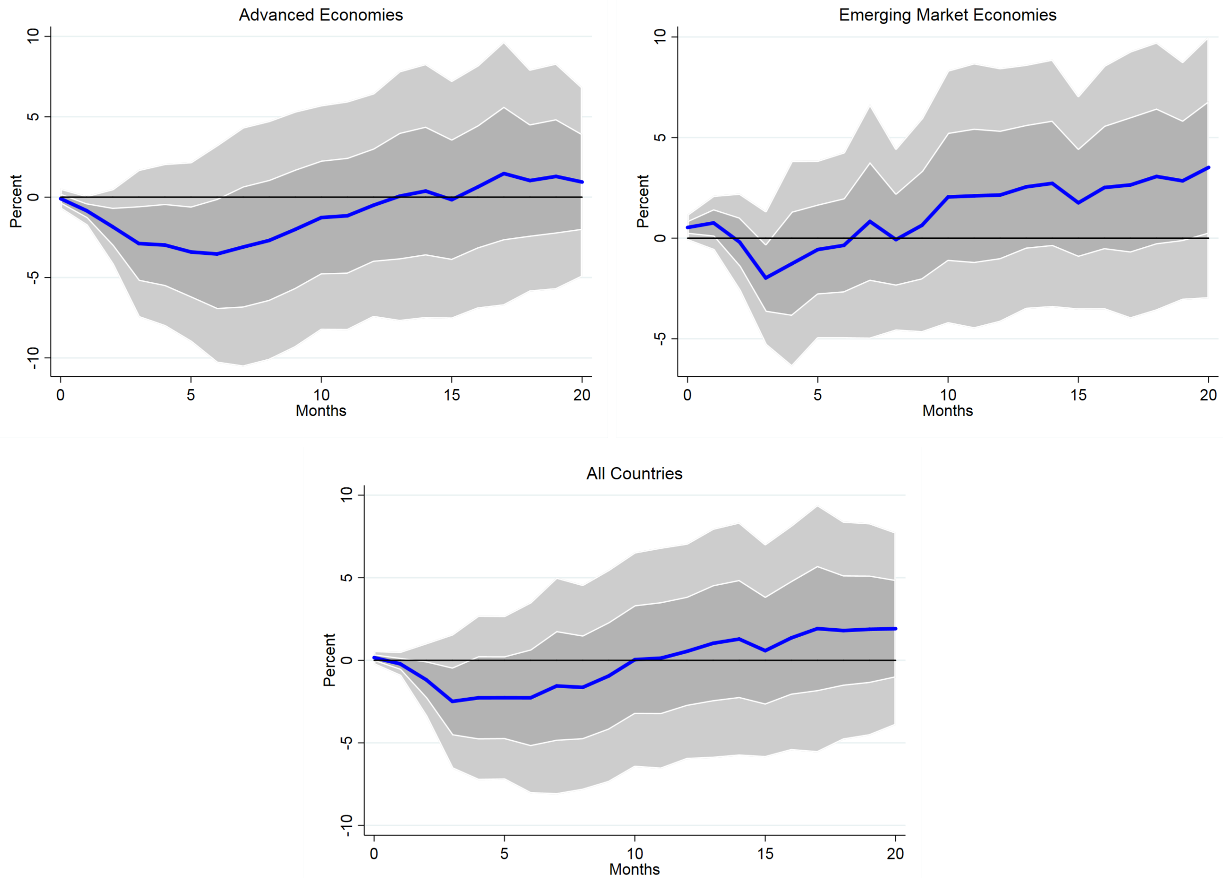
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval. In the case of government stability, high implies less stable. High government debt sustainability means more sustainable debt. High current account balance means higher current account deficit. For the financial development measures, high means more developed.

Figure 14: Effect of GFRUi on countries' industrial production: USD Peg and Vulnerability indexes from Iacoviello and Navarro



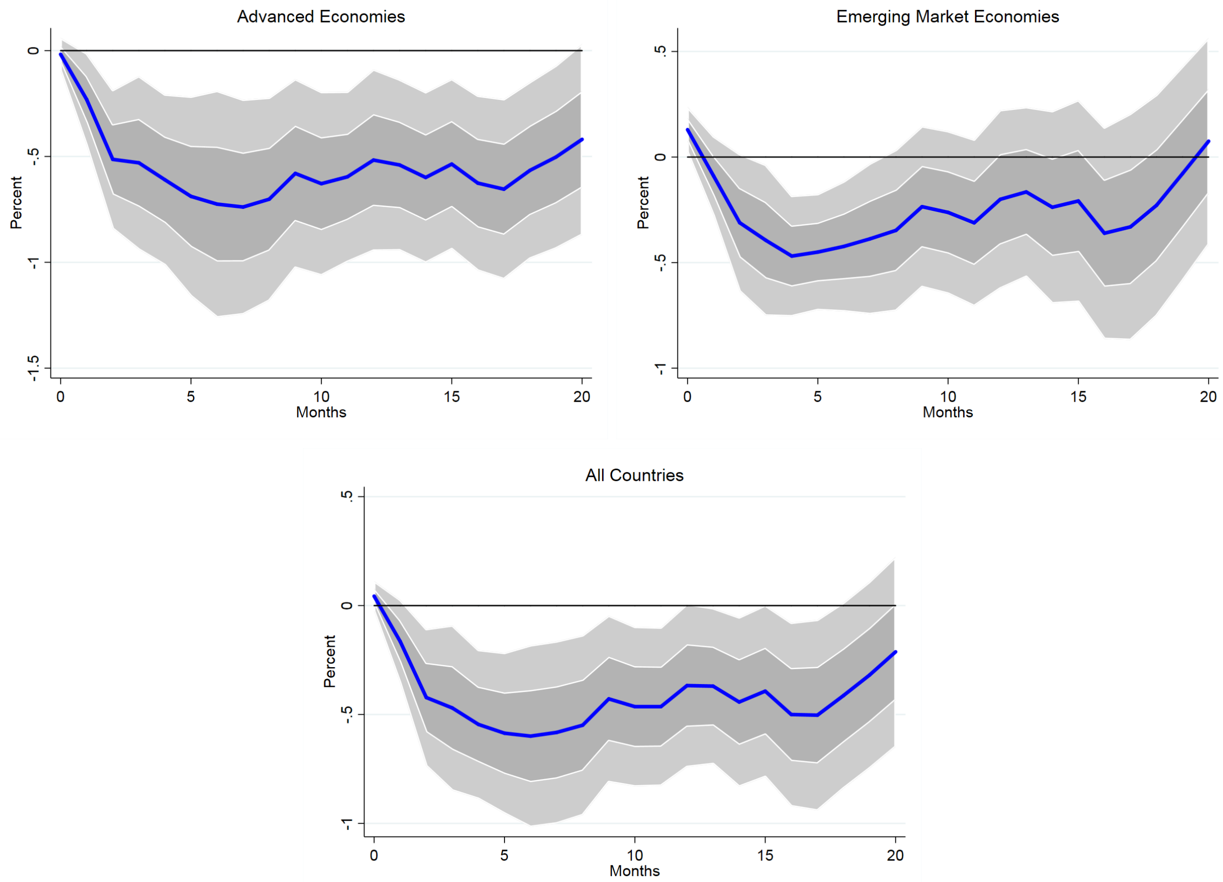
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval.

Figure 15: Robustness: Effect of a shock to the GFRUi on industrial production: IV approach



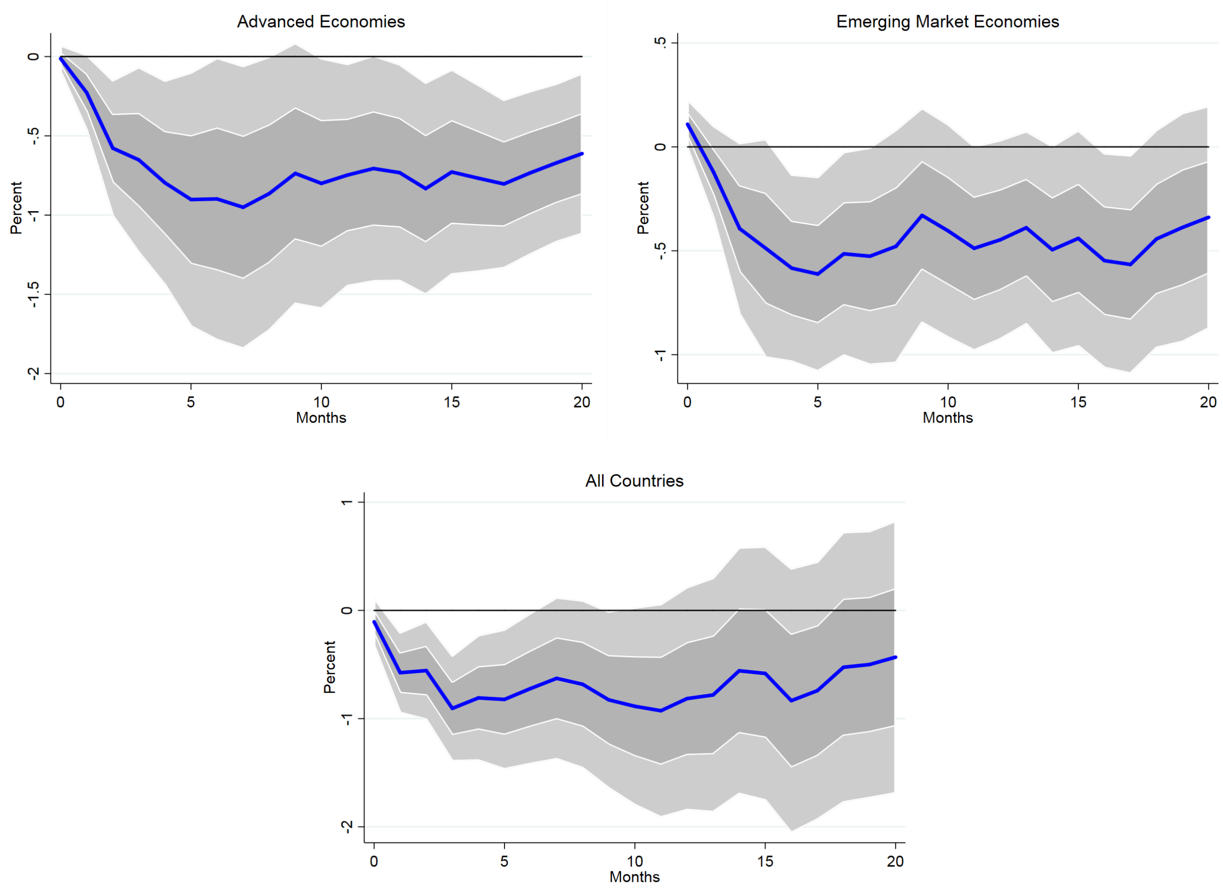
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. Gray area represents 68% and 95% confidence intervals computed using Driscoll and Kraay (1995) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 16: Robustness: Effect of GFRUi on industrial production - controlling for oil prices and ea monetary policy



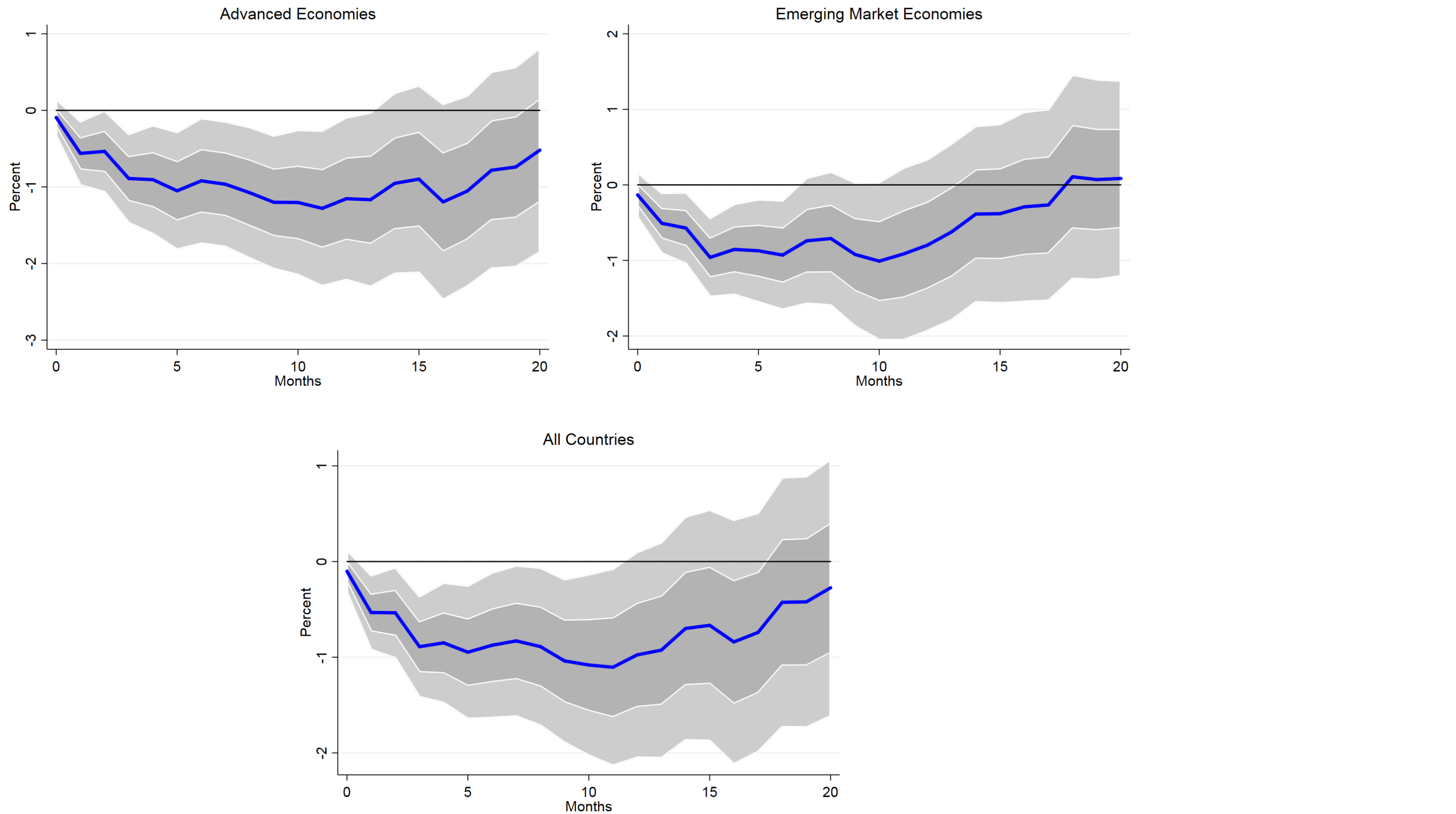
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. This specification of the baseline model includes the oil price and the short-term interest rate for the euro area. Gray area represents 68% and 95% confidence interval computed using Driscoll and Kraay (1995) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 17: Robustness: Effect of GFRUi on industrial production - 6 lags regression



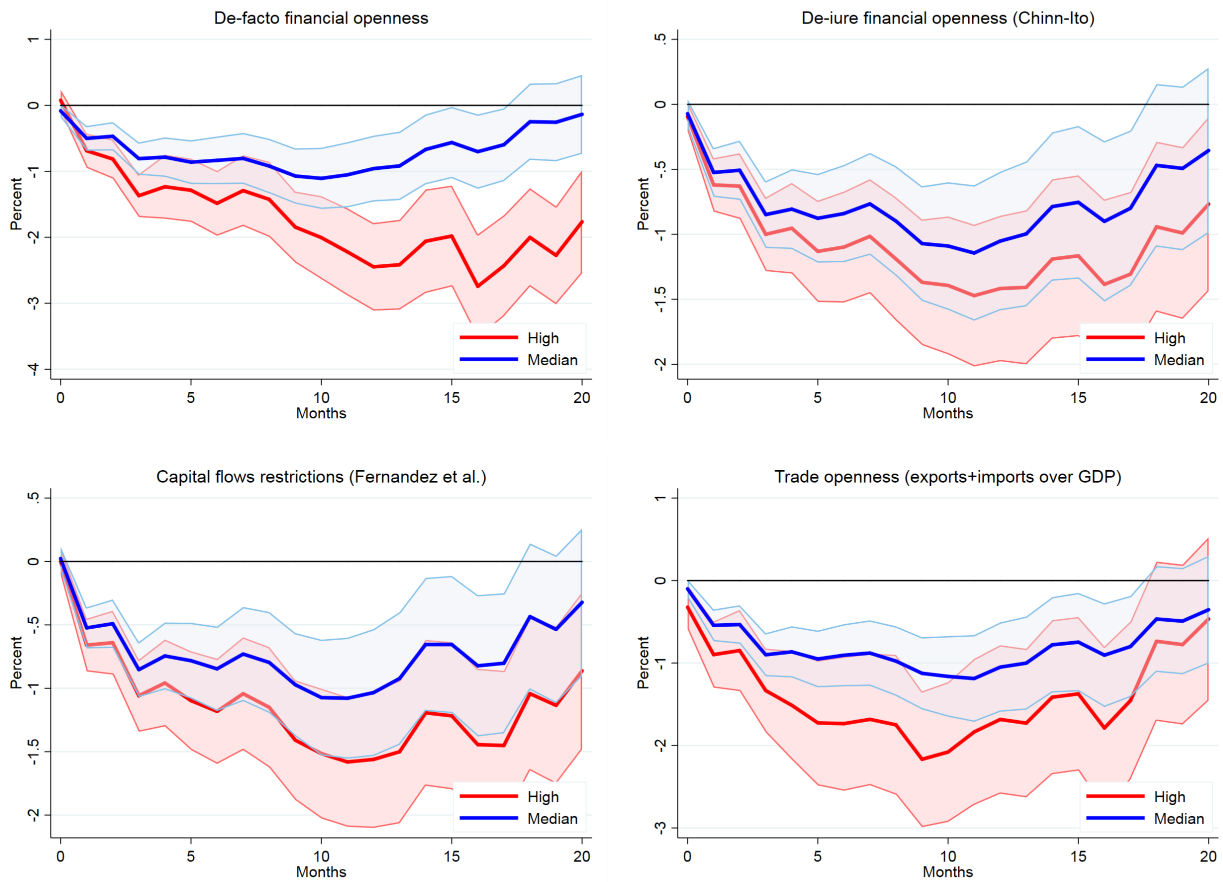
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUi on industrial production. This specification of the baseline model includes 6 lags rather than 4 for the regressors. Gray area represents 68% and 95% confidence intervals computed using Driscoll and Kraay (1995) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 18: Robustness: Effect of a shock to the Global Financial Cycle Index on industrial production



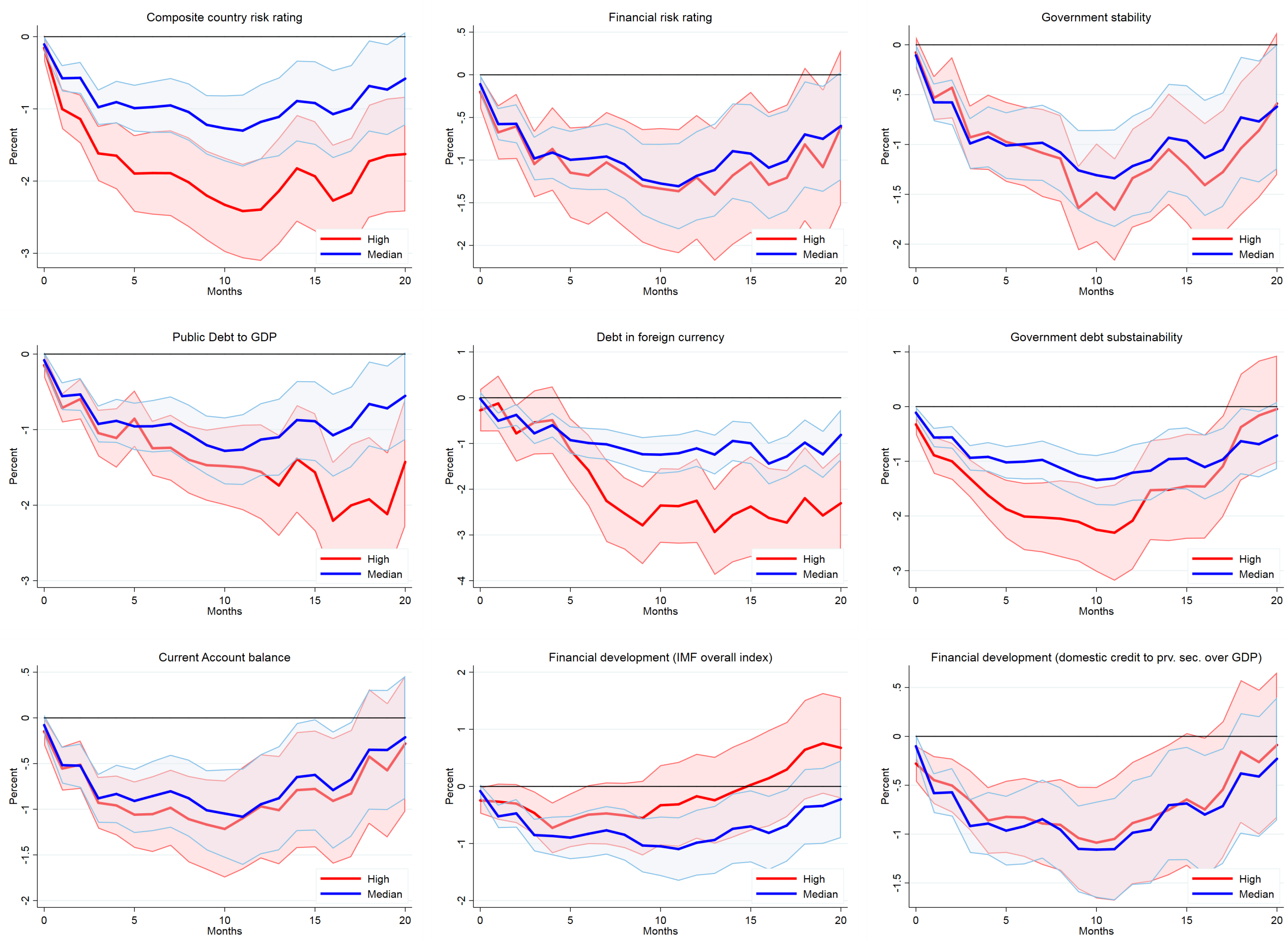
Note: The figure shows the effect of a 1 std.dev. shock in the Global Financial Cycle Index on industrial production. Gray area represents 68% and 95% confidence intervals computed using Driscoll and Kraay (1995) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 19: Effect of Global Financial Cycle Index on countries' industrial production: integration and openness



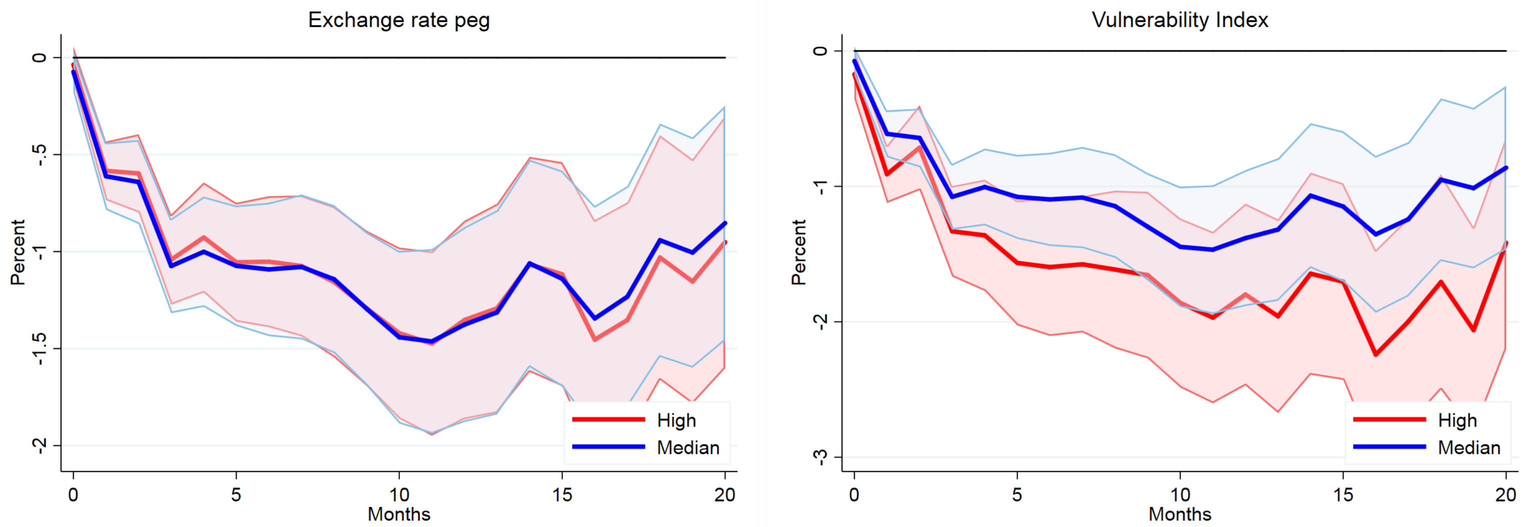
Note: The figure shows the effect of a 1 std.dev. shock in the Global financial cycle index on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval. For de-facto financial openness we excluded Luxembourg and Ireland from the sample due to the extraordinary high level of the index for both countries. Results are still robust to the inclusion of those countries. High in the case of capital flows restrictions means a more open capital account.

Figure 20: Effect of Global Financial Cycle Index on countries' industrial production: vulnerabilities



Note: The figure shows the effect of a 1 std.dev. shock in the Global financial cycle index on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval. In the case of government stability, high implies less stable. High government debt sustainability means more sustainable debt. High current account balance means higher current account deficit. For the financial development measures, high means more developed.

Figure 21: Effect of Global Financial Cycle Index on countries' industrial production: USD Peg and Vulnerability indexes from Iacoviello and Navarro



Note: The figure shows the effect of a 1 std.dev. shock in the Global Financial Cycle Index on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval.

C Construction of the Weighted Indexes

The measures of global output and global prices for are constructed as a weighted average of the indexes of industrial production and CPI of all the countries in our data sample as follows:

$$X_{t,j} = \Sigma^j \omega_j x_{t,j} \tag{C.1}$$

where ω_j are PPP weights of country j. The weights are taken from the IMF-WEO database.

D Construction of the Global Financial Conditions Index

The underlying dataset used to derive the GFCi is the same one used to estimate the GFRUi. Following Stock and Watson (2002) and Bai and Ng (2002), we assume that financial data $x_{i,t}$ are characterised by a factor structure of this form:

$$x_{i,t} = \lambda_i^{'} F_t + \varepsilon_{i,t}, \quad i = 1, ...N \tag{D.1}$$

where F_t is a vector collecting all common factors, $\varepsilon_{i,t}$ is an idiosyncratic shock and λ_i is a vector of common factors loadings. As required by factor analysis, prior to extracting the factors, data are stationarised, while outliers are removed following the procedure used by Eickmeier et al. (2014).[18] The factors are obtained using principal component analysis. The first principal component explains 38% of the variation in global risky assets. The GFCi is obtained by taking a cumulative sum of the factor estimated on first-differenced data and, as in MA-R, we argue

[18] Outlier adjustment entails replacing data with absolute median deviations larger than 3 times the interquartile range with the median value of the 5 preceding observations.

that this factor summarises changes in global financial conditions.[19] This becomes especially apparent in Figure 3, where we plot the GFRUi series against the NBER recessions and some important economic and the global factor by MA-R. As can be seen from the figure, the GFRUi tends to spike during periods of turmoils in financial markets. The factor is scaled such that an increase represents a tightening of financial conditions around the world.

[19]Specifically, MA-R use a theoretical model to identify the factor as being representative of global financial risk and uncertainty. They show that the factor incorporates two separate components that can be interpreted as realised volatility in global traded assets and the level of risk appetite of international investors (both global banks and fund managers).