

Boncianni, Dario; Ricci, Martino

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Dario Bonciani, Martino Ricci The global effects of global risk and uncertainty

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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 global factor, which explains approximately 40% of the variance of about 1000 risky asset returns from around the world. We then study how shocks to the factor affect economic activity in 36 advanced and emerging small open economies by estimating local projections in a panel regression framework. We find the output responses to be 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 higher levels of external debt, less developed financial sectors, and higher risk rating.

Keywords: Global Financial Cycle; Local Projection; Macroeconomic Transmission; Panel Data.

JEL-Classification: C30, F41, E32, F65.

Non-Technical Summary

The Great Recession contributed in shifting economists' attention towards new potential drivers of macroeconomic fluctuations, such as shocks originating in the financial sector as well as disturbances to the level of aggregate uncertainty. At the same time, the global dimension of the crisis underscored once more how interconnected the world has become over the last thirty years. In this new environment, a growing body of literature has documented the existence of a global financial cycle which can potentially have important real implications for individual countries. However, the literature has hitherto mainly focused on understanding the drivers of the global financial cycle, while its real effects have not been yet thoroughly assessed, especially for small open economies.

From a monetary policy perspective, the existence of a global financial cycle has important implications as this puts into question the “Mundellian trilemma”, i.e. the idea that a country cannot contemporaneously achieve a fixed foreign exchange rate, free capital movement and independent monetary policy. Understanding the transmission of global financial shocks is therefore of utmost importance in order to refine policy instruments apt at facing them.

In this paper, we identify a measure of global financial conditions and quantify empirically its effects on the real economy. We do this on a panel of 36 small open economies, almost equally distributed between advanced and emerging economies, using monthly data spanning from January 1990 until December 2015. More specifically, the global financial cycle is estimated as the factor that explains the largest share (approximately 40%) of the variation in about 1000 risky asset returns around the world. We show that our measure tends to spike during certain events that caused turmoils in the global financial markets and argue that fluctuations in the cycle mainly reflect changes in global uncertainty and risk aversion. Yet, when compared to other

competing measures of risk aversion and uncertainty, such as the VIX, we find the correlation not to be particularly high (about 25%). In order to quantify the real effects of global financial shocks, we run panel regressions and estimate local projections. The local projection method shows as being more robust to model misspecifications than standard impulse responses and easily allows us to calculate state-dependent responses.

From our empirical investigation, it emerges that on average a tightening in global financial conditions significantly worsens real economic activity in a persistent manner, yet the sign, size, and persistence of these effects are rather heterogeneous across countries.

We do not find a significant difference between advanced and emerging economies. However, we show that country-related factors, such as weak macroeconomic fundamentals (e.g. high external debt) and higher financial and trade openness can explain the heterogeneity of the responses. These results suggest that policymakers should aim at reducing vulnerabilities, such as the level of external debt, to make their countries more resilient to global financial tightenings. However, they also face a trade-off between the long-term growth advantages of opening up to trade and to the financial markets and the short-term risks mentioned above. This evidence further informs the discussion on the desirability of coordinating policy responses around the world.

1 Introduction

Over the last 30 years, we have witnessed a dramatic increase in financial globalization. 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 conditions on economic activity (industrial production) for a wide range of small open economies, 19 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, which is similar yet more comprehensive than the one used in MA-R. We find that one single factor, which we label as the global financial risk and uncertainty index (hereafter GFRUI), explains around 40 per cent of the total variance in our data. Second, we quantify the effects of shocks to the GFRUI on economic activity in 36 small open economies, which by assumption take the GFRUI as exogenous. To this end, we estimate Local Projections à la [Jorda \(2005\)](#) with panel regressions and find that a tightening of global financial conditions significantly worsens real economic activity in a persistent manner. These effects are rather heterogeneous across

countries. We find a stronger impact in countries with weaker macroeconomic fundamentals (e.g. high external debt) and in those with higher financial and trade openness. We show that our results are robust to several 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.

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](#)). For the construction of the GFRUI, our methodology is closely related to MA-R, though we consider a different and broader dataset. 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 at its consequences on real activity. More specifically, our main contribution is analysing how the global financial factor 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 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.

¹What we do in the paper is to 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 in local stochastic discount factors.

From an empirical point of view, the literature has found that increases in 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 \(2015\)](#) analyses 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. 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 esti-

mate 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 consists of three main parts. In the first one, we define the strategy adopted to obtain the GFRUI and the data we used. In the second, we outline the model used to estimate the effects of the GFRUI on our sample. Last, we explain how we identify the key transmission channels through which the GFRUI affects small open economies.

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. 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.² Further details on the series contained in our dataset can be found in Table 1. Data are collected on a monthly basis from December 1989 to July 2017. 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:

$$x_{i,t} = \lambda_i' F_t + \varepsilon_{i,t}, \quad i = 1, \dots, N \quad (1)$$

²An 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.

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. \(2014\)](#).³ The factors are obtained using principal component analysis. The first principal component explains 38% of the variation in global risky assets. The GFRUI is obtained by taking a cumulative sum of the factor estimated on first-differenced data and, as in MA-R, we argue that this factor summarises changes in global risk and uncertainty.⁴ This becomes especially apparent in Figure 1, where we plot the GFRUI series against the NBER recessions and some important economic and political events from 1990 to 2017. As can be seen from the figure, the GFRUI tends to spike during events that cause turmoils in financial markets.⁵ Our GFRUI index is strongly correlated (over 90%) with the global factor in risky asset returns estimated by MA-R.⁶ Figure 2 compares the GFRUI with some selected indexes of global uncertainty and risk aversion. Interestingly, the profile of the factor often overlaps with that of these other measures considered, signalling that it does a good job at describing changes in financial conditions. However, the correlation with the VIX (0.26) is not particularly high, suggesting that our measure captures some overall conditions in global financial markets which are not reflected by movements in the VIX and hence are likely to originate outside the US.

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

⁴Specifically, 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).

⁵We decide to scale the factor such that an increase represents a tightening of financial conditions around the world.

⁶Note that, differently from us, MA-R use a dynamic factor model with regional blocks to clean the factor from potential disturbances related to regional shocks. Notwithstanding, the correlation of the GFRUI with their global factor is very high and the profile almost identical (see figure 2).

2.2 Estimating the GFRUI Impact

2.2.1 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-depended 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):

$$IRF(t, h, d_i) \equiv \mathbb{E}[Y_{t+h}|v_t = d_i; S_t] - \mathbb{E}[Y_{t+h}|v_t = 0; S_t] \quad (2)$$

where: $E[\cdot]$ is conditional expectation function; 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_t 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. As an example of the LPM for Panel Data, consider the following fixed-effects regression (3):

$$Y_{i,t+h} = \alpha_{i,h} + A_{i,h}(L) Y_{i,t-1} + \gamma_{i,h} Z_t + B_{i,h}(L) X_{i,t-1} + C_h(L) Z_{t-1} + \varepsilon_{i,t+h}. \quad (3)$$

In the regression equation (3), Y is the dependent variable, X is the set of controls, Z is the shock variable and ε is the error term. 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 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 $(\hat{\gamma}_h)_{h=0}^H$. 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 this 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.

We identify the effects of the GFRUI on the local variables in line with the literature on uncertainty shocks, assuming that global uncertainty is contemporaneously affected by the other

global variables included in the controls and by US monetary policy. In particular, the global variables enter the regression both at time t and with their lags, while the local variables enter only with a lag. Global variables are therefore predetermined compared to the local variables. The identification is therefore equivalent to assuming a Cholesky decomposition in which the GFRUI is ordered last with respect to the global variables. We run the following regression with country fixed-effects:

$$Y_{i,t+h} = \alpha_{i,h} + A_{i,h}(L) Y_{i,t-1} + \gamma_{i,h} Z_t + B_{i,h}^{Local}(L) X_{i,t-1}^{Local} + B_{i,h}^{Global}(L) X_t^{Global} + C_h(L) Z_{t-1} + \varepsilon_{i,t+h}. \quad (4)$$

In equation (4), $Y_{i,t}$ is the industrial production of country i , Z_t is the GFRUI. X_{t-1}^{Local} is a set of domestic control variables (specifically, short-term interest rates and inflation). The vector of global control variables X_t^{Global} includes the federal funds rate, to control for developments in US monetary policy, a measure of global output and CPI which allow us to control for developments in global demand and supply. In particular, we construct the control variables for each country as a weighted average of industrial production and CPI of all the countries in the data sample as follows:

$$X_{t,i} = \sum^j \omega_{i,j} x_{t,j} \quad (5)$$

where $\omega_{i,j}$ are bilateral trade weights of country i with respect to country j . We follow this approach, borrowed from the GVAR literature, to better capture the way global real developments might impact the country under scrutiny. Finally, we include a time trend and 4 lags in our regression, although, adding more lags does not significantly change the results (unsurprisingly

given that local projections do not impose dynamic restrictions on the IRFs, see section 3.3 for further details).

2.2.2 Data Description

In order to estimate the effects of the GFRUI on the global economy we collect macroeconomic data for 36 countries, almost equally distributed between advanced and emerging economies: Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Italy, Japan, Korea, Latvia, Lithuania, Malaysia, Mexico, Netherlands, Norway, the Philippines, Poland, Portugal, Russia, South Africa, Spain, Sweden, Thailand, Turkey and the United Kingdom.⁷ We consider monthly data for industrial production (our proxy for output), CPI inflation and short-term interest rates, spanning from 1991 until 2015 (conditional on data availability). The data is obtained from national sources or international institutions (i.e. OECD or IMF (IFS)). 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;⁸ (ii) it deals with various consistency issues concerning seasonal adjustments and industrial classification.⁹

⁷The classification of advanced and emerging economies is consistent with the one provided by the IMF in the World Economic Outlook.

⁸The following countries are missing from the CPB database and are replaced with other sources: Chile (start 2009, source OECD), Colombia (start 1991, source Haver Analytics) Malaysia (start 1991, source Haver Analytics, industrial production excluding construction) the Philippines (start 1998, source Haver Analytics) South Africa (start 1991, source BIS) Thailand (start 2011, source Haver Analytics).

⁹Further details on the construction of the dataset can be found on the CPB website: <https://www.cpb.nl/en/data>.

2.2.3 Identifying the Transmission Determinants

As a baseline exercise, we first estimate panel local projections by running the fixed-effects regression described in (4). Additionally, we complement this exercise by running separate panel regressions for advanced and emerging economies. 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.¹⁰ To this end, we collect several indexes related to country openness and vulnerabilities: **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 and the (vi) financial risk rating from the International Country Risk Guide (ICRG); (vii) current account-to-GDP-ratio and (viii) external debt-to-total debt ratio; (ix) IMF overall index of financial development and (x) domestic credit to the private sector-to-GDP ratio as an additional measure of financial development. All of these indexes span from 1990 until 2015, with the exception of the kai index which starts in 1995. Data are collected using the database of international linkages (*IntLink*) developed by the ECB in the context of the International Linkages

¹⁰We 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 from of a monetary policy shock in the US.

and Spill-overs Network.¹¹

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:

$$Y_{i,t+h} = \alpha_{i,h} + A_{i,h}(L)Y_{i,t-1} + \gamma_{i,h}GFRUI_t + \gamma_{i,h}^v(e_{i,t}^v GFRUI_t)^\perp + \Gamma_h(L)GFRUI_{t-1} + B_{i,h}^{Local}(L)X_{i,t-1}^{Local} + B_{i,h}^{Global}(L)X_t^{Global} + \varepsilon_{i,t+h}. \quad (6)$$

Hence we augment the baseline regression (4) by an interaction term between the GFRUI and a function of the variable of openness or vulnerability, $e_{i,t}^v$. In particular, along the lines of Iacoviello and Navarro (2018), the latter is constructed in four steps: (i) we standardise the measure of openness/vulnerability, $s_{i,t} = \frac{\text{indicator}_t - \text{mean}(\text{indicator})}{\text{var}(\text{indicator})}$; (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, $l_{i,t}^p = \frac{l_{i,t}^p - l_i^{50}}{l_i^{95} - l_i^{50}}$; finally (iv), we regress each characteristic $l_{i,t}^p$ on all the regressors of (4) and keep the residual $e_{i,t}^v$. The rationale behind the aforementioned 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 $\gamma_{i,h} + \gamma_{i,h}^v$ 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 $e_{i,t}^v$ orthogonal to the regressors in equation (4), thus ensuring that the coefficient estimates of (6) are going to be same to those in the baseline, except for the interaction term, which can be interpreted as the marginal contribution of the characteristic

¹¹The codebook of the database is available at: https://www.ecb.europa.eu/home/pdf/research/intlink/db/Code_Book_Intlink.pdf?76bbc1267568e3e3f6ae6643339a7696.

under study.

3 Results

3.1 The Impact of Global Financial Risk and Uncertainty

Figure 3 presents the response to the shock for the model presented in (4). The average response to the shock is negative, persistent and statistically significant over the considered horizon. 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 big differences do not emerge from this exercise, the shock has a smaller impact on emerging markets and unwinds more rapidly.

In order 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.¹² Figures 8 and 9 help us summarise the results and eye-ball 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. Countries in the American (both North and South) continent experience a decline of industrial production in the order of 2%, with the exception of Chile, whose response is relatively more subdued. In Europe, Lithuania, Estonia, the Czech Republic and particularly Hungary (-3.4%) are the most affected by the shock, while Italy and

¹²Figures 4 to 7 show the impulse response functions for all the countries in the sample to a one standard deviation increase in the GFRUI, which is interpreted as a tightening of global financial conditions induced by an increase in risk and uncertainty.

France exhibit rather weak responses. Results are mixed also for Asia and Oceania: Thailand, Malaysia, and Japan suffer the most from a global financial tightening while Australia, Russia, and China are relatively shielded from it. All in all, no clear picture emerges from the analysis of 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 the countries, the median response is negative, suggesting that the shock does not wind up quickly. However, for some countries, specifically Belgium, Turkey, Russia, Thailand, Malaysia and South Korea, 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. \(2017\)](#)).

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 (6) described in section 2. Figures 10 and 11 show the results of this exercise. In particular, 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 - For 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 inter-linkages 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 or the index provided by [Fernández et al. \(2016\)](#), we find the responses under financial openness to be about twice as large as in the baseline scenario. Using the Chinn-Ito index of *de iure* capital account openness, the effects are larger than in the baseline scenario, yet the difference is economically less significant. The results on trade, go in the same direction. Openness to trade implies a response that is roughly twice as large as in the baseline scenario. The significance of these estimates varies with the indicator chosen. Alternative robustness checks (presented in section 3.3) tend to confirm the importance of openness measures for the transmission of the shock.

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,¹³ the level of the current account over GDP, two measures of countries' indebtedness and two different indicators of financial development. We find that countries with a higher composite risk rating and a higher level of debt (particularly in foreign currency) are hit by the shock more severely (nearly twice larger than the baseline case). We find evidence that a less developed financial sector is also an important factor, which leads to roughly a 50% stronger decline in economic activity than in the

¹³Notice 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.

baseline scenario. The other factors instead, do not affect the responses in a significant way.

3.3 Alternative model specifications

In this subsection, we discuss various changes to the main empirical exercises to test the robustness of our results. First, we include oil prices as an additional regressor in our model, 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 and oil price shocks.

As a second robustness check, we include a measure of Euro Area (EA) short-term interest rates to control for the ECB's monetary policy, contemporaneously determined to the GFRUI. In particular, we construct a measure of EA interest rate from 1989 until 1999, similarly as in the Area Wide Model of the EABCN, and use the EONIA rate for the post-1999 sample.

As a third robustness exercise, we consider how decreasing the number of lags to 2 or increasing it to 6 affects our results. Since local projections do not impose any dynamic restrictions on the IRFs, we do not expect these changes to have major effects. Figures 12 to 14 display the results from the various robustness exercises. The profile of the IRFs is substantially unaffected by the various robustness exercises conducted.

Finally, in order to benchmark our results to other measures, we consider a shock to the VIX rather than to our measure of global risk and uncertainty. The VIX index is a measure of implied volatility that has been used extensively in the macroeconomic literature as an indicator of global risk and uncertainty. The results for this exercise, shown in figure 15 are in line with the

literature on the topic: an increase in the VIX has a negative impact on the industrial production of advanced and emerging economies. We find that a one standard deviation shock to the VIX causes a significant and persistent decline in economic activity by approximately 0.5% both in advanced and emerging economies. Compared to the baseline results, the output responses are weaker than those to a GFRUI shock (about half). Also in this case, we do not find major differences in the response profile for advanced and emerging market economies. Moreover, when we repeat our analysis aimed at singling out the various transmission determinants of the shock (figures 16 and 17), we do not find supporting evidence for the importance of most of the characteristic considered. This may be suggesting that the underlying nature of the shocks driving the VIX and the GFRUI is different. In particular, the VIX may be more affected by US-specific factors than the GFRUI, which has a more global dimension by construction. These speculations are worth further investigation, yet they would go beyond the scope of our paper and we leave them to future research.

4 Conclusion

In this paper, we investigate how a tightening in global financial conditions affects economic activity, using a panel of 36 small open economies. To this end, we first extract a global factor from a large data-set of financial risky asset prices and argue this factor to be mainly driven by fluctuations in uncertainty and risk aversion. We then study its impact on economic activity by estimating local projections based on a panel regression model with country fixed effects. We find that shocks increasing the GFRUI (which worsen financial conditions) strongly and persistently dampen 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 weaker macroeconomic fundamentals (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 a global financial tightening. 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

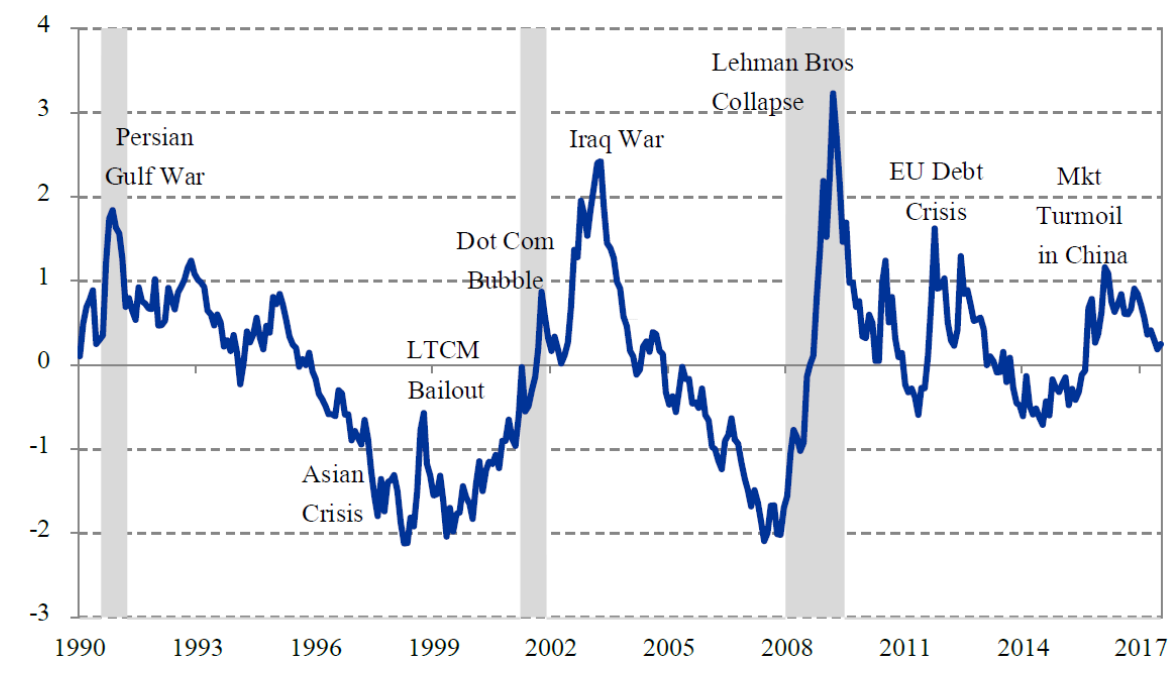
Table 1: Financial series included in the estimation of the GFRUI

Region:	<i>America</i>	<i>United States</i>	<i>Europe</i>	<i>Asia</i>	<i>Commodities</i>	<i>Banks</i>	<i>Oceania</i>
Series:	164	162	158	139	40	73	69

Note: The table reports the number of series used to compute the GFRUI divided 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.

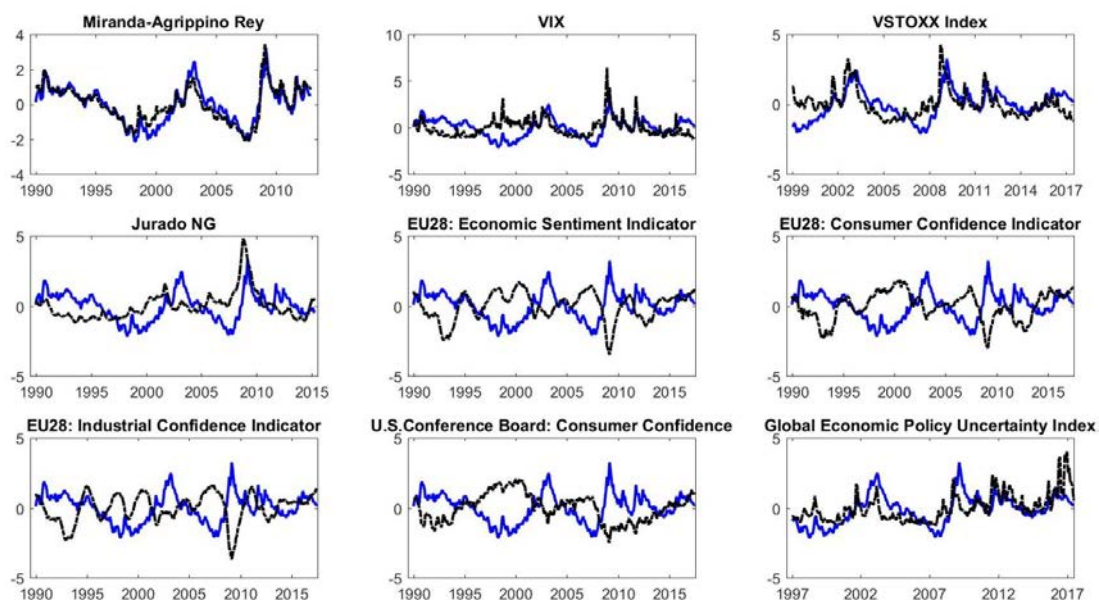
B Figures

Figure 1: The Global Financial Risk and Uncertainty Index



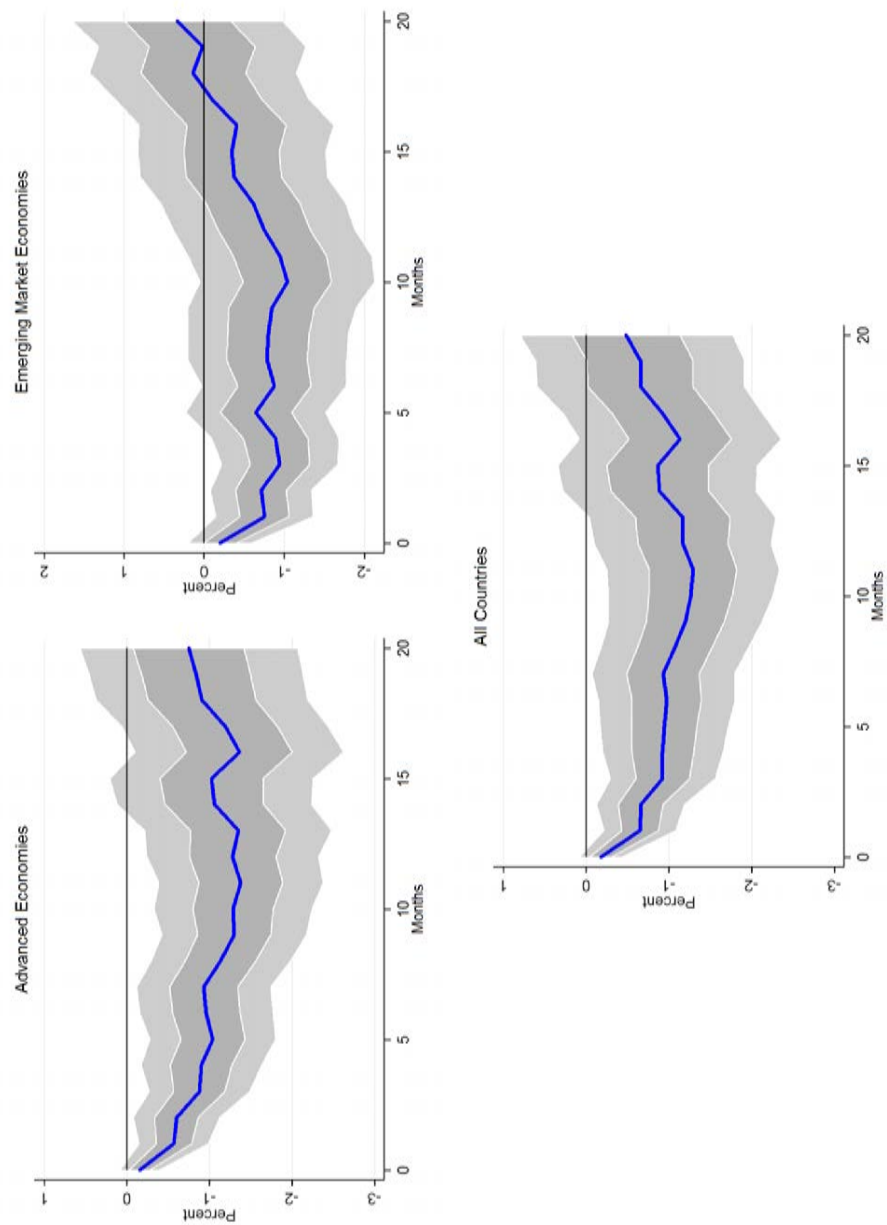
Note: The Global Financial Risk and Uncertainty Index plotted vis-à-vis some important political and economic events from January 1990 to July 2017. Shaded areas represent NBER recessions for the U.S.

Figure 2: GFRUI correlation with indexes of volatility and uncertainty



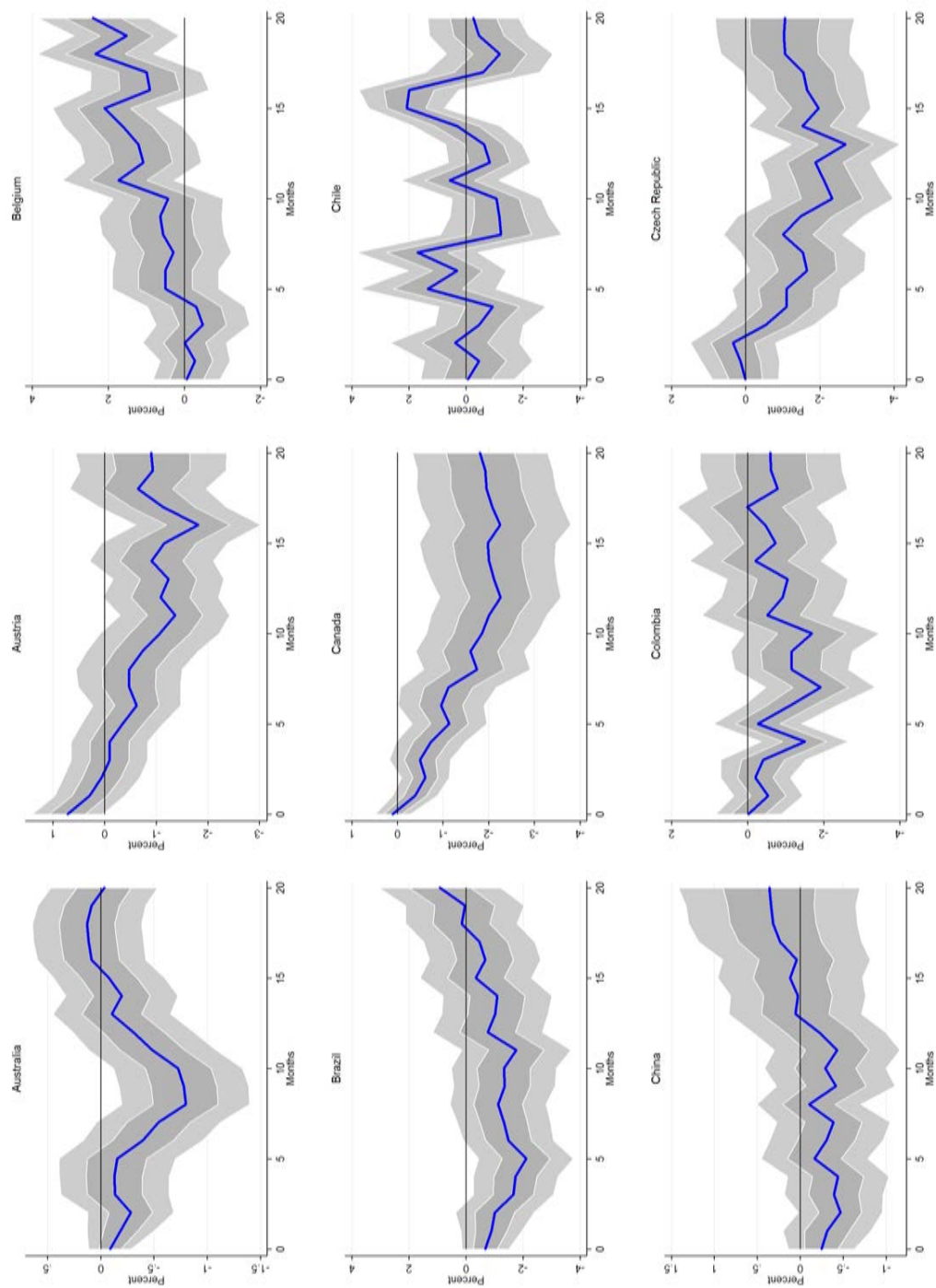
Note: The figure displays the GFRUI and selected indexes of volatility and uncertainty. All indices have been standardised to facilitate the comparison. The correlation between the GFRUI and the other indices are as follows: Miranda-Agrippino Rey 0.9, CBOE VIX 0.26, VSTOXX Index 0.51, Jurado NG 0.21, EU econ. sent. -0.64, EU 28 Consumer conf -0.62, EU industrial confidence -0.54, US consumer confidence -0.68, Global Economic Policy Uncertainty Index 0.54.

Figure 3: Effect of GFRUI on industrial production



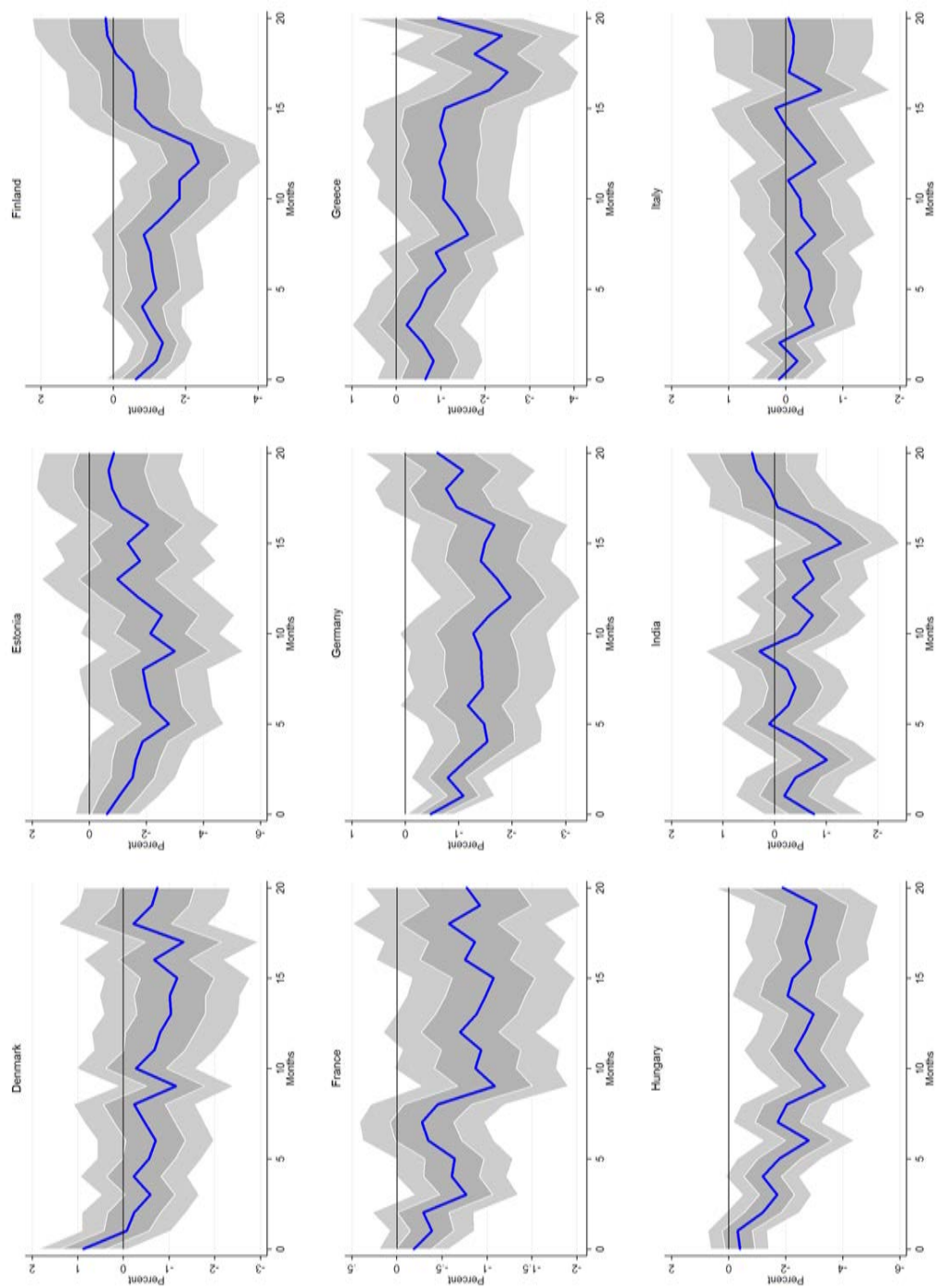
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. Gray area represents 68% and 95% confidence interval computed using [Driscoll and Kraay \(1995\)](#) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 4: Effect of GFRUI on countries' industrial production



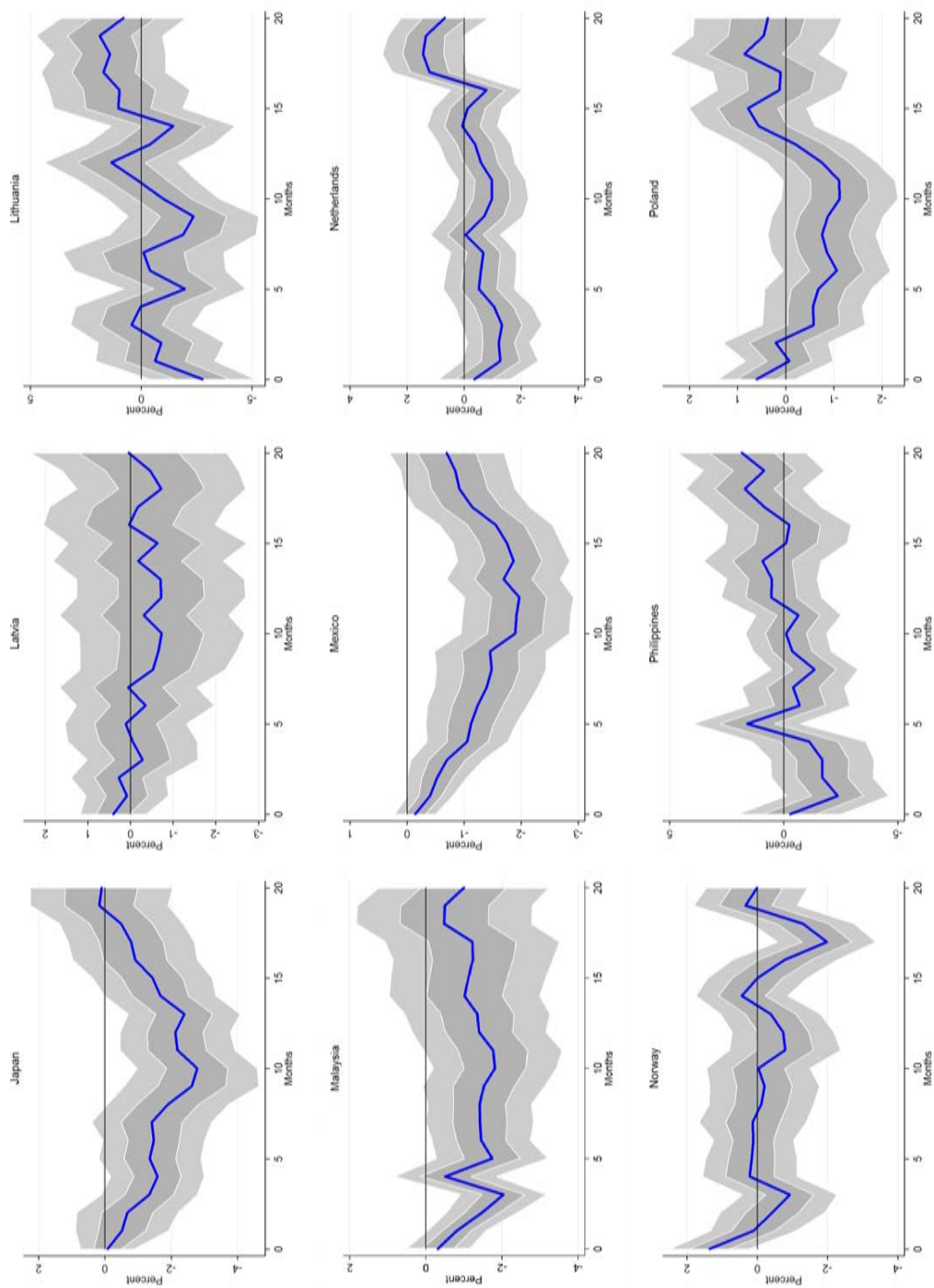
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. Gray area represents 68% and 95% confidence interval, computed using Newey-West HAC standard errors.

Figure 5: Effect of GFRUI on countries' industrial production



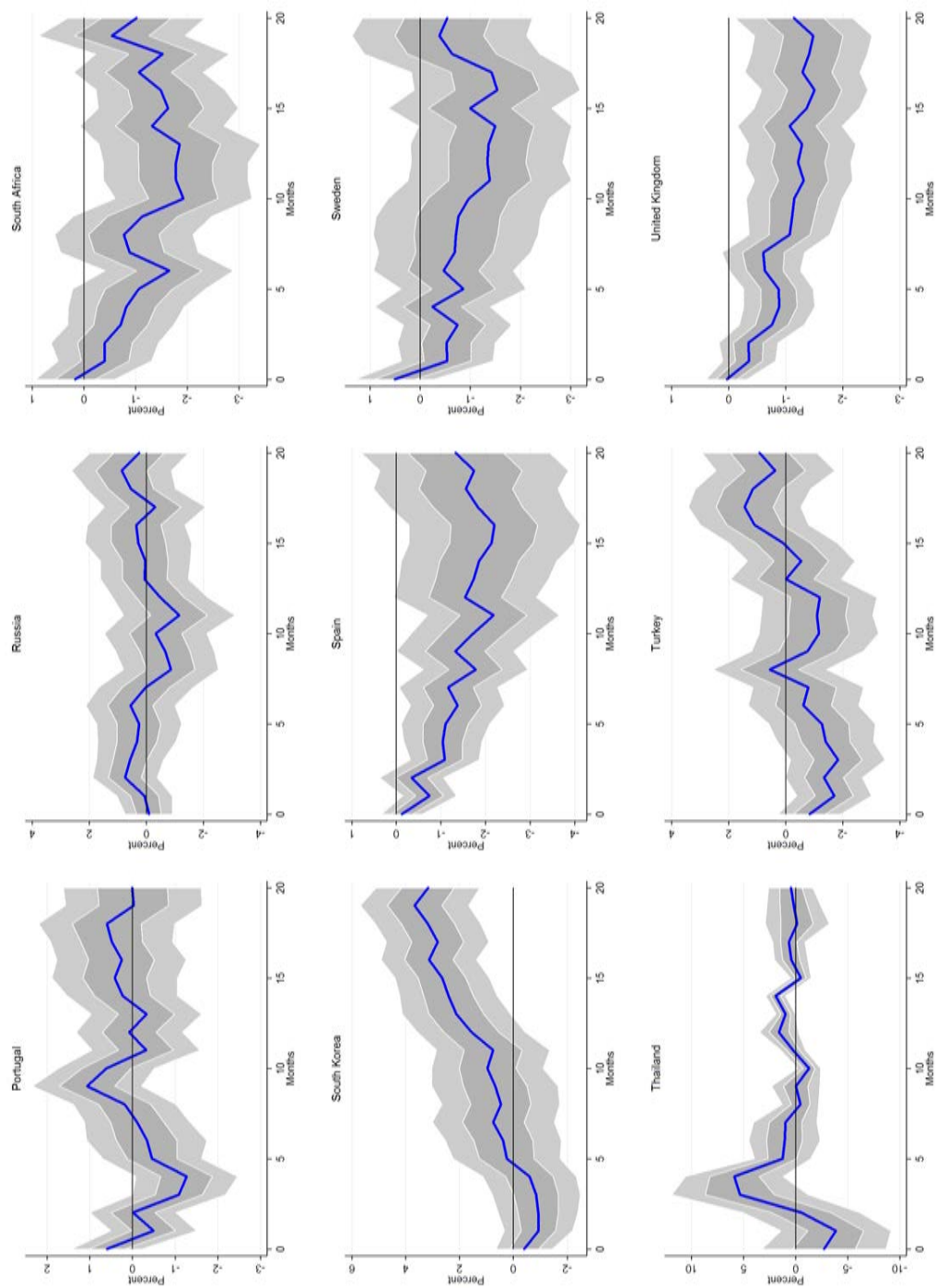
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. Gray area represents 68% and 95% confidence interval, computed using Newey-West HAC standard errors.

Figure 6: Effect of GFRUI on countries' industrial production



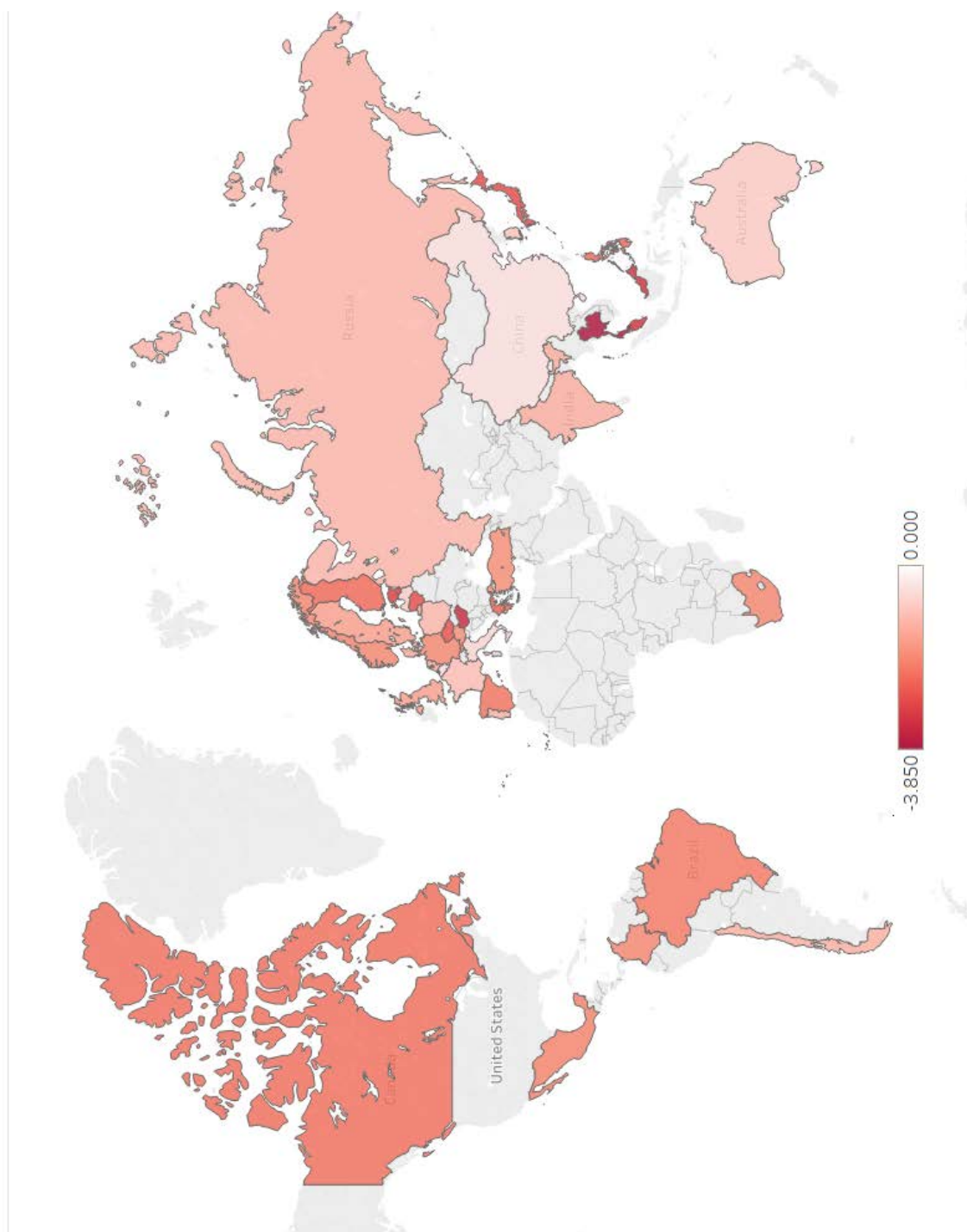
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. Gray area represents 68% and 95% confidence interval, computed using Newey-West HAC standard errors.

Figure 7: Effect of GFRUI on countries' industrial production



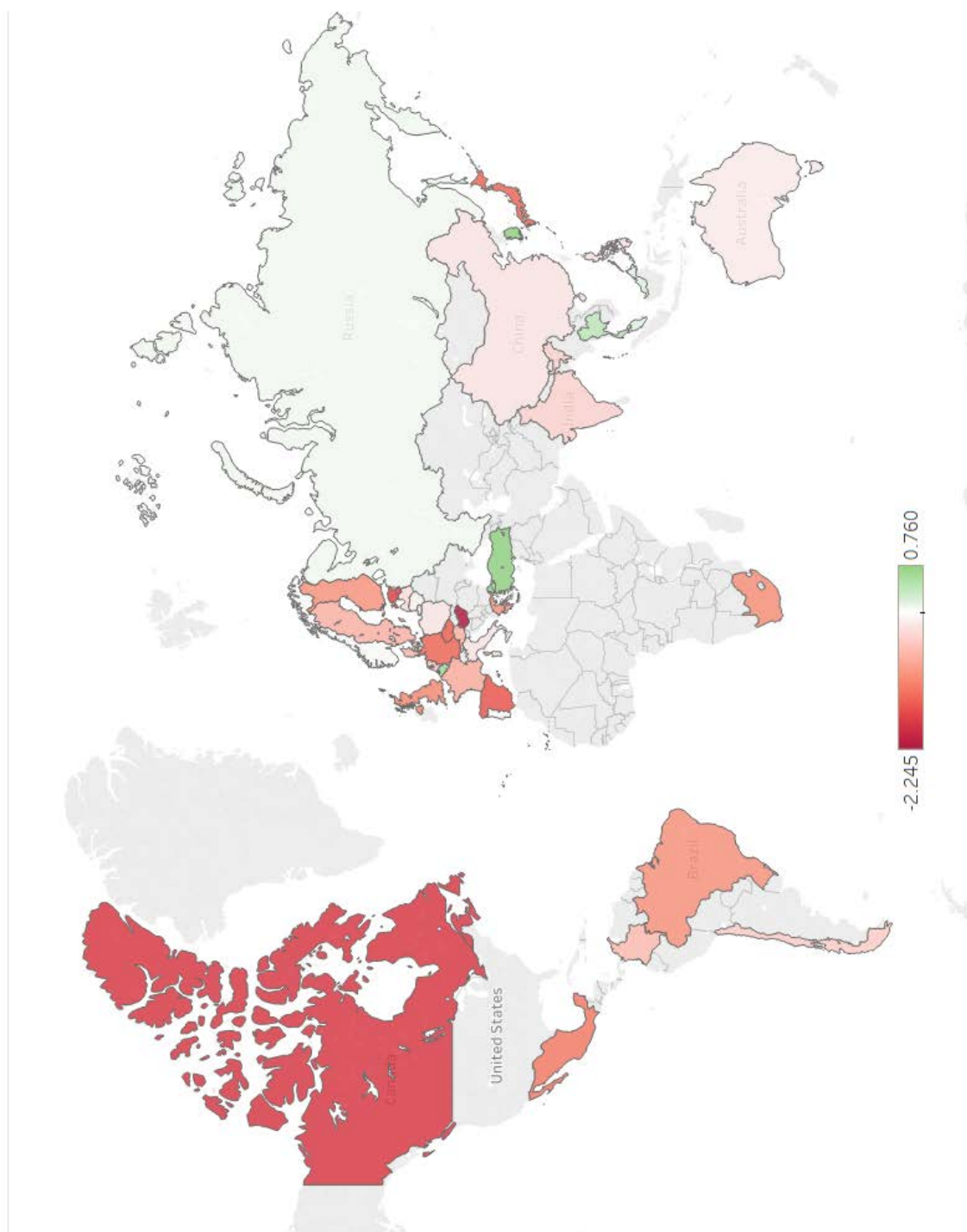
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. Gray area represents 68% and 95% confidence interval, computed using Newey-West HAC standard errors.

Figure 8: Effect of GFRUI on countries' industrial production: trough response.



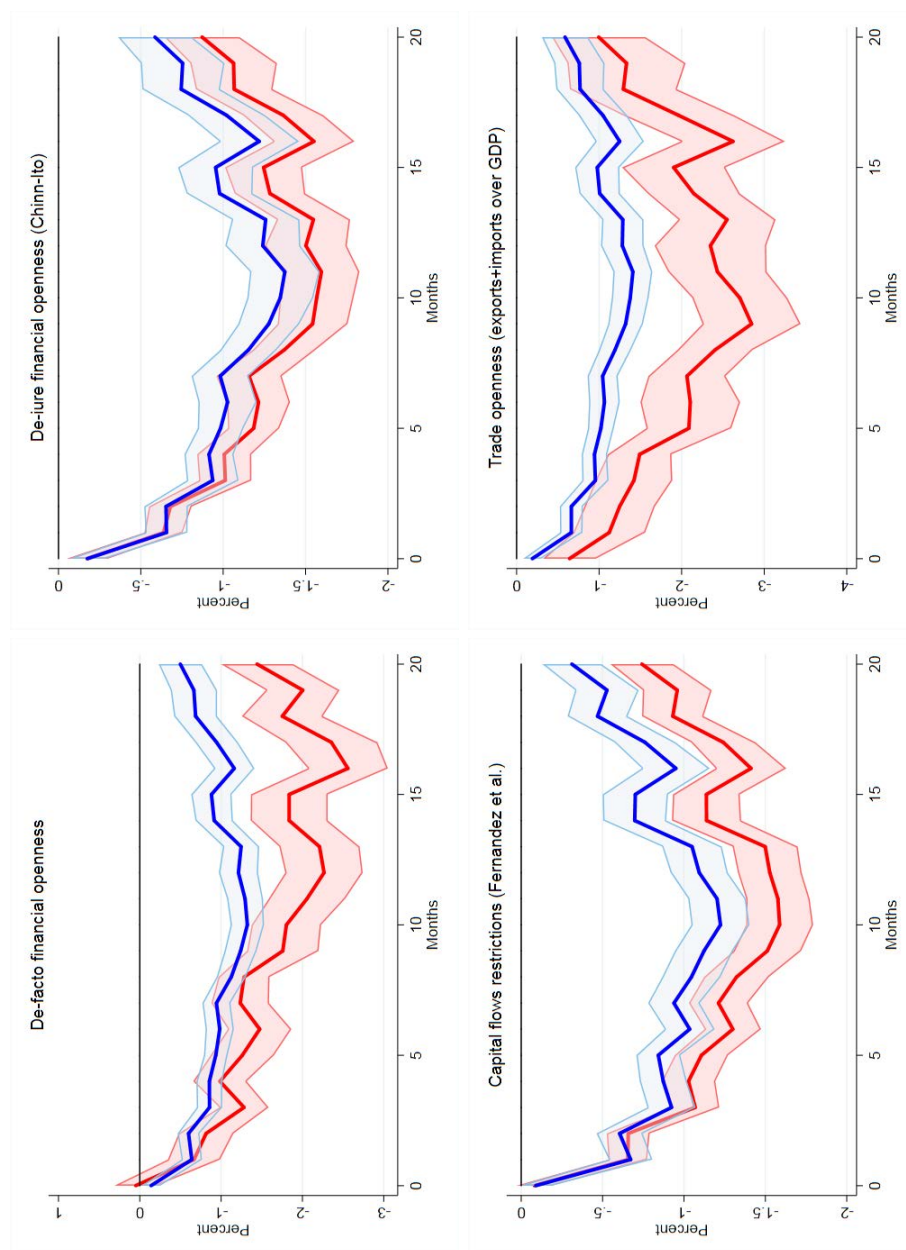
Note: The figure shows the trough response in industrial production for the countries in the sample for a 1 standard deviation shock in the GFRUI.

Figure 9: Effect of GFRUI on countries' industrial production: median response.



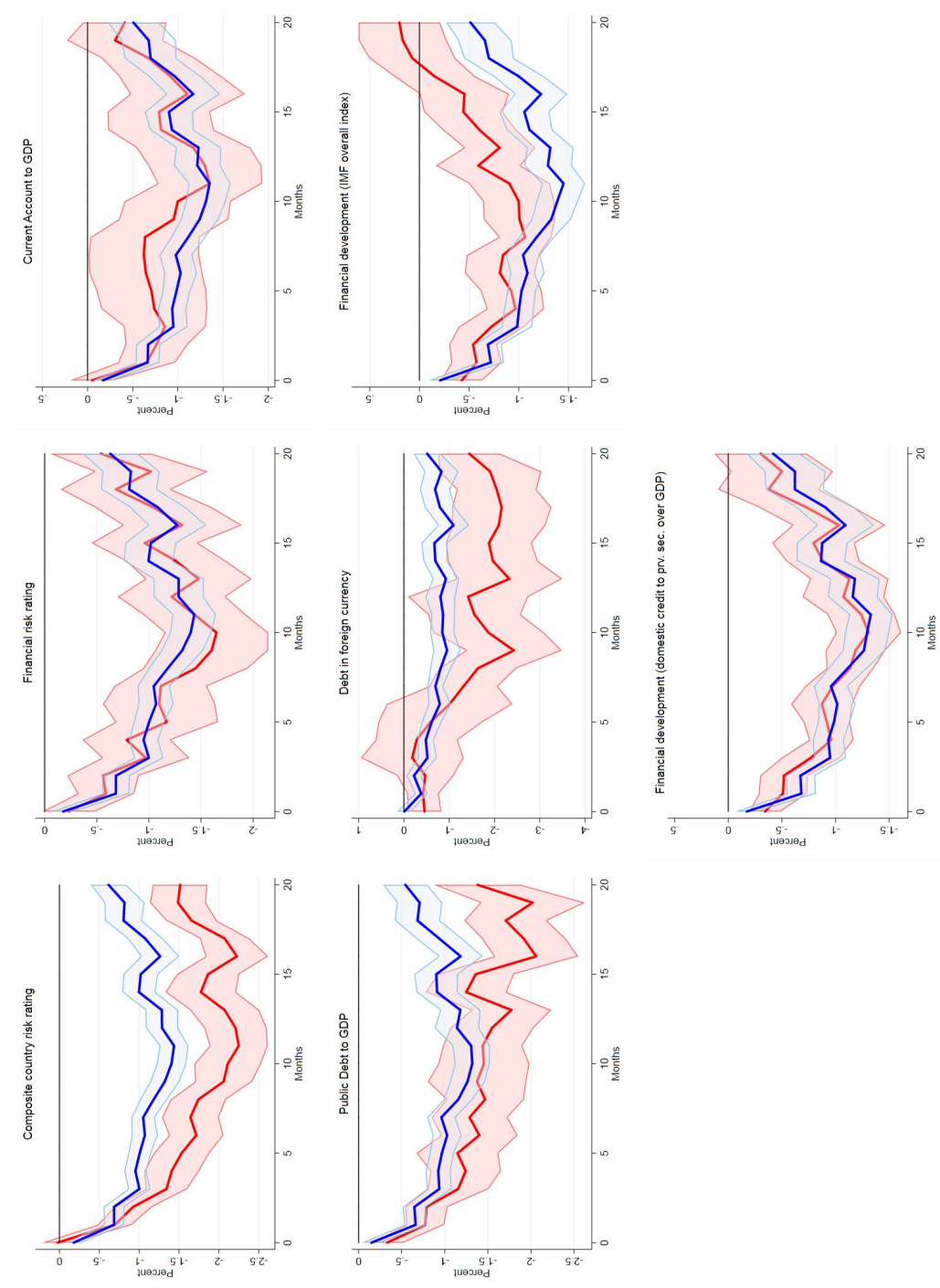
Note: The figure shows the median response in industrial production for the countries in the sample for a 1 standard deviation shock in the GFRUI.

Figure 10: Effect of GFRUI on countries' industrial production: integration and openness



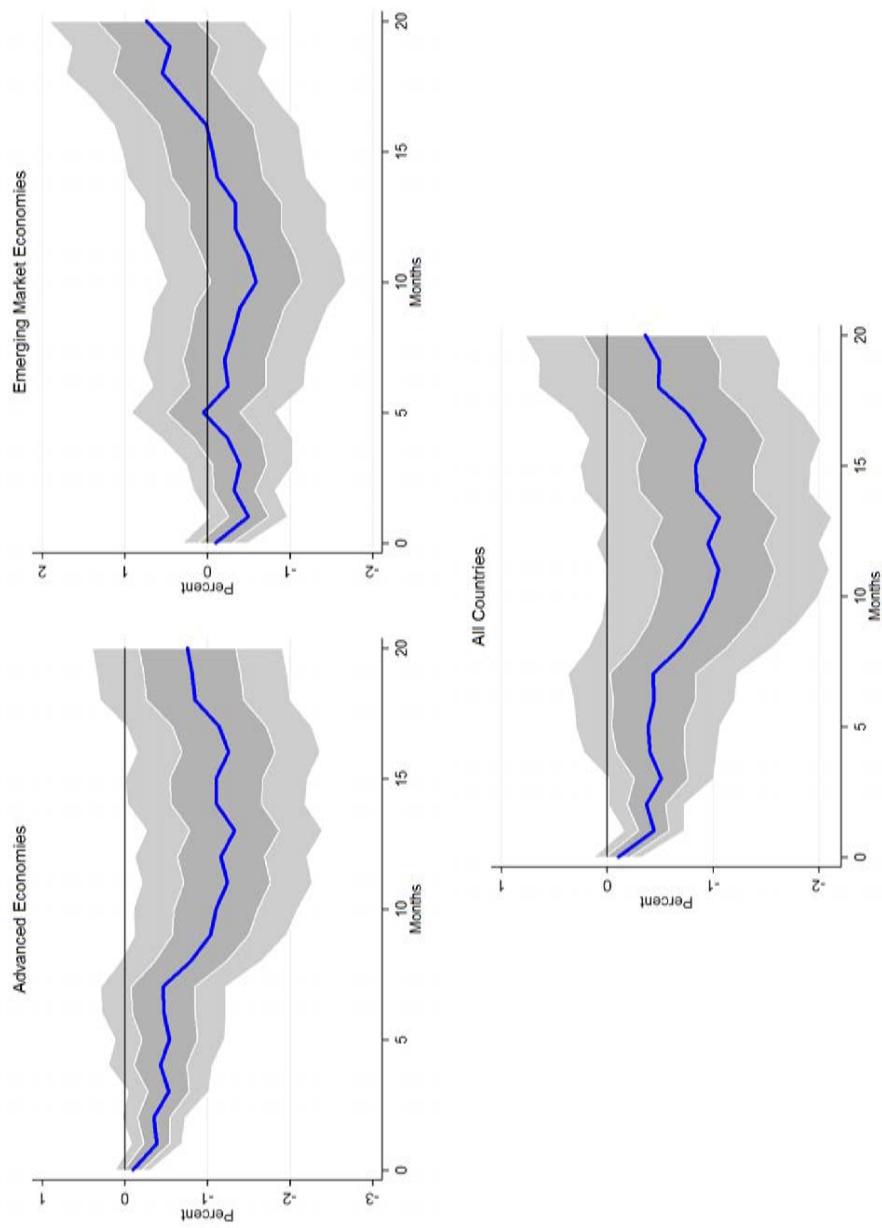
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval.

Figure 11: Effect of GFRUI on countries' industrial production: vulnerabilities



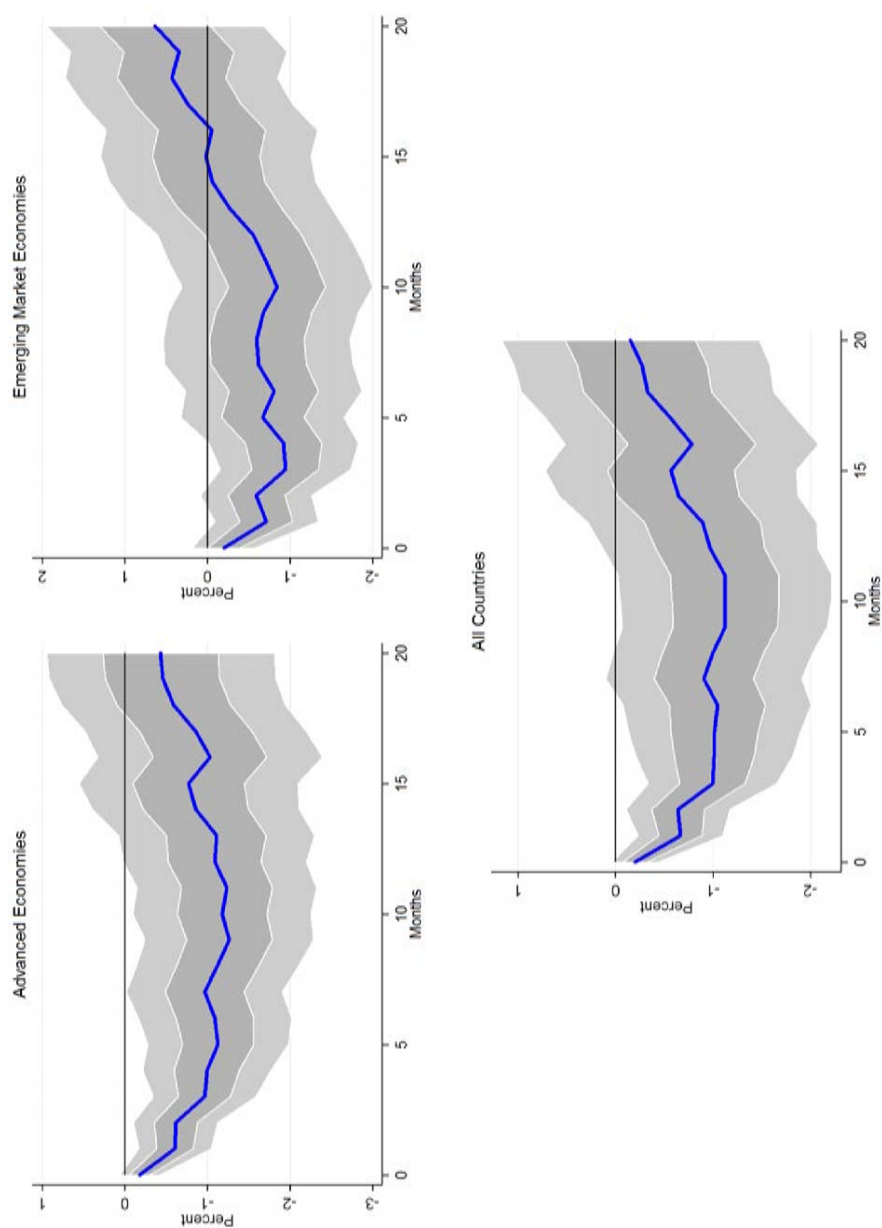
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. The blue/red lines are the responses to the shock when the characteristic considered is at its median/95th percentile. Shaded areas represent 68% confidence interval.

Figure 12: Robustness: Effect of GFRUI on industrial production - alternative model specification



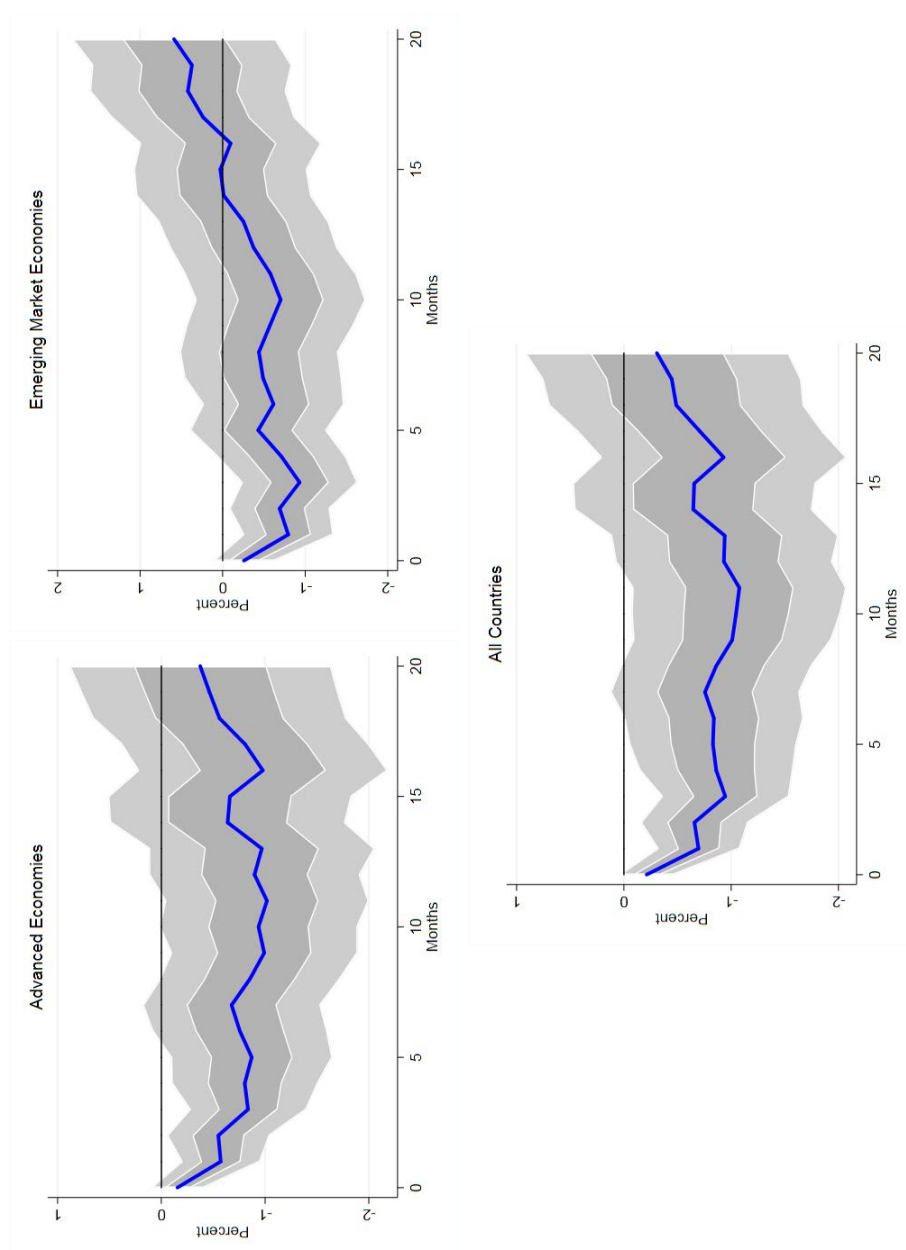
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. This specification of the baseline model includes the oil price and short-term interest rate for the euro area. Gray area represents 68% and 95% confidence interval computed using [Driscoll and Kraay \(1995\)](#)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

Figure 13: Robustness: Effect of GFRUI on industrial production - alternative lag structure



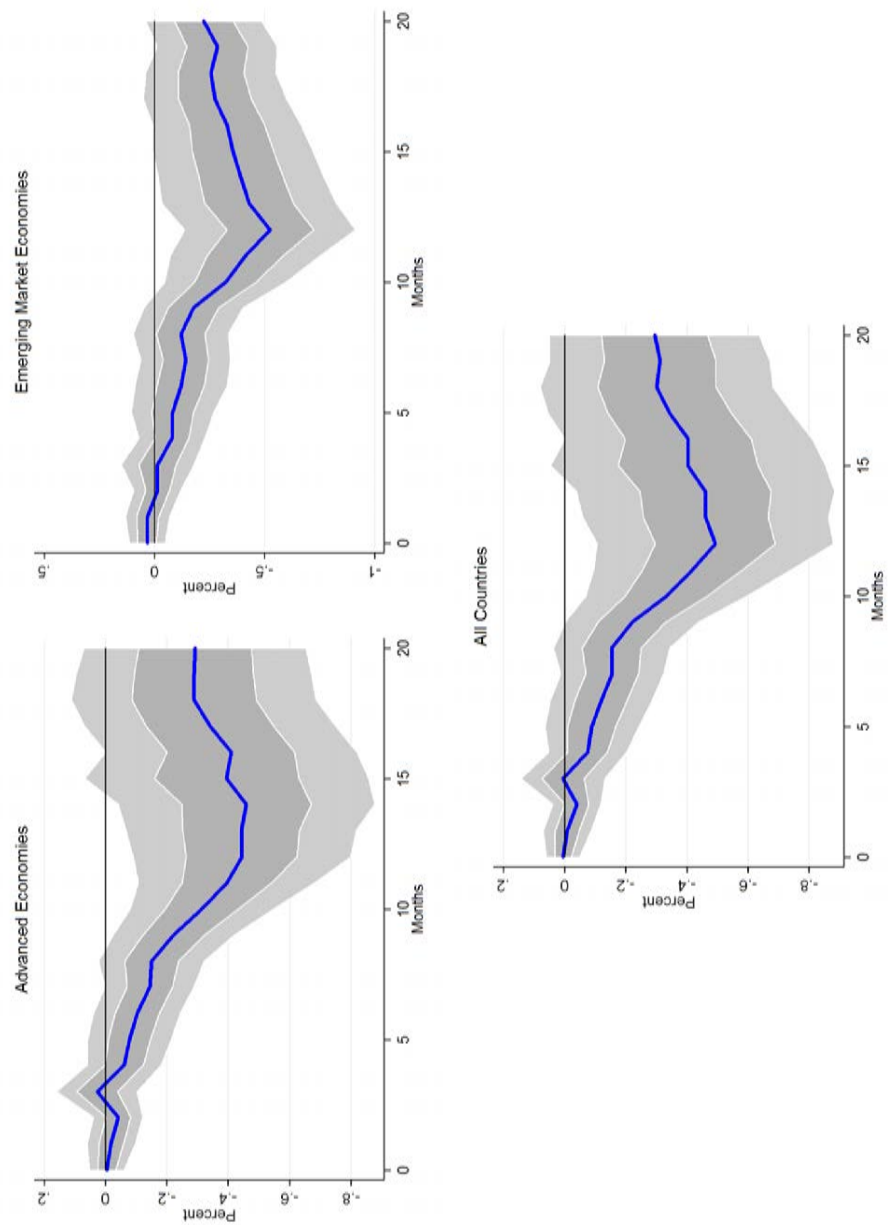
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. This specification of the baseline model includes 2 lags rather than 4 for the regressors. Gray area represents 68% and 95% confidence interval computed using [Driscoll and Kraay \(1995\)](#) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 14: Robustness: Effect of GFRUI on industrial production - alternative lag structure



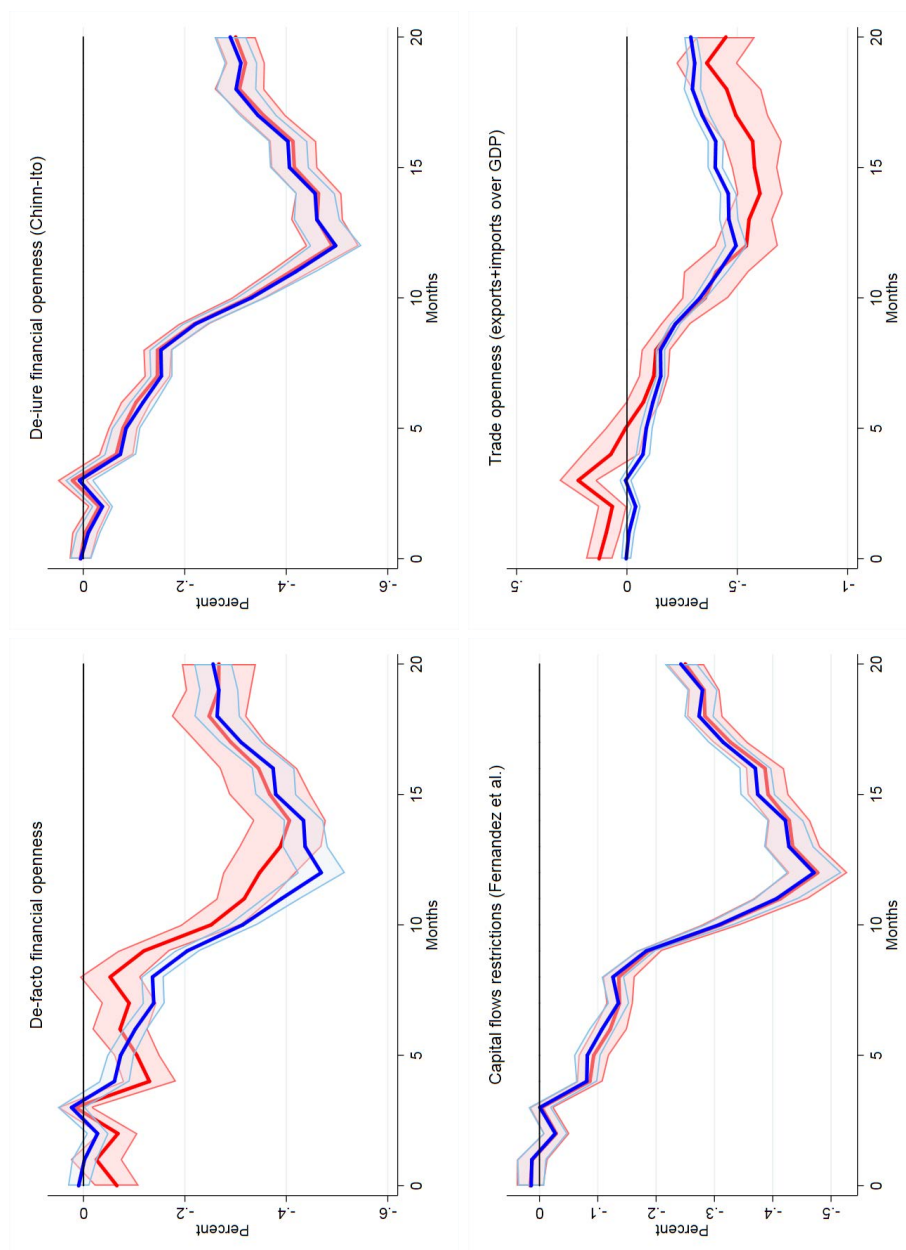
Note: The figure shows the effect of a 1 std.dev. shock in the GFRUI on industrial production. This specification of the baseline model includes 6 lags rather than 4 for the regressors. Gray area represents 68% and 95% confidence interval computed using [Driscoll and Kraay \(1995\)](#) standard errors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

Figure 15: Robustness: Effect of a VIX shock on industrial production



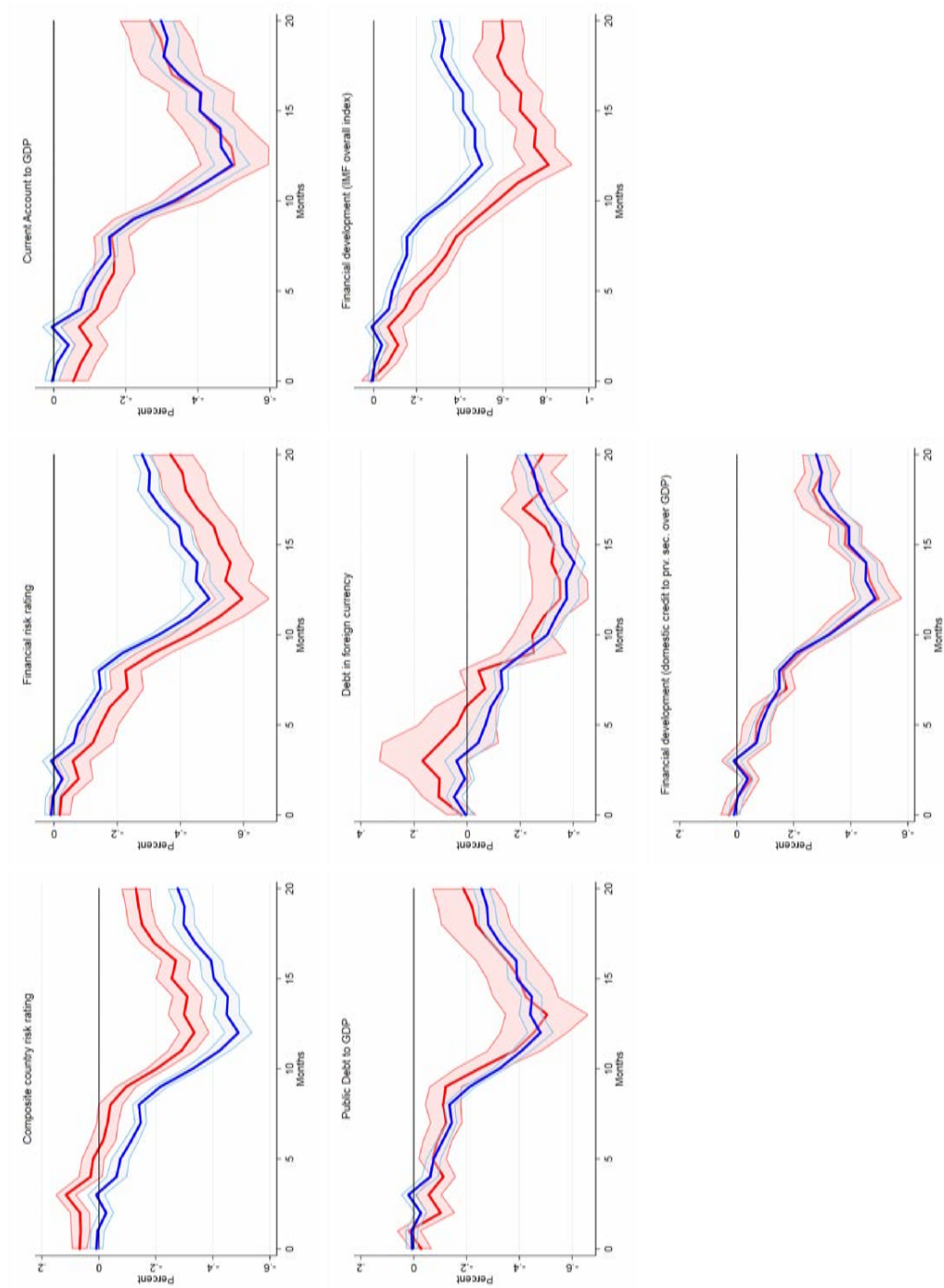
Note: The figure shows the effect of a 1 std.dev. shock in the VIX on industrial production. Gray area represents 68% and 95% confidence interval computed using [Driscoll and Kraay \(1995\)](#) standard errors that are robust to heteroskedasticity, serial and spatial correlation.

Figure 16: Effect of VIX on countries' industrial production: integration and openness



Note: The figure shows the effect of a 1 std.dev. shock in the VIX 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 17: Effect of VIX on countries' industrial production: vulnerabilities



Note: The figure shows the effect of a 1 std.dev. shock in the VIX 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.

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Dario Bonciani

European University Institute, Florence, Italy; email: dario.bonciani@eui.eu

Martino Ricci

European Central Bank, Frankfurt am Main, Germany; email: martino.ricci@ecb.int

© European Central Bank, 2018

Postal address 60640 Frankfurt am Main, Germany

Telephone +49 69 1344 0

Website www.ecb.europa.eu

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