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Vulnerable funding in the global economy

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ABSTRACT

This study builds on the conceptual framework of vulnerable growth to examine how US financial shocks influence the conditional distribution of real credit growth across a diverse set of countries, a phenomenon we term *vulnerable funding*. We show that deteriorating US financial conditions are linked to a reduction in real credit growth abroad, with particularly pronounced effects at the lower quantiles of real credit growth abroad. This suggests that, in common with the episodes of vulnerable growth discussed in the extant literature, episodes of vulnerable funding are also triggered globally by financial weakness in the US. However, our analysis reveals significant variation in the impact of US financial shocks across the quantiles of credit growth in countries worldwide. Specifically, countries with lower credit-to-GDP ratios or with higher levels of US investment relative to their GDP exhibit greater real credit growth vulnerability.

1. Introduction

The recent literature has highlighted the significant predictive power of domestic financial conditions on real economic activity during periods of macroeconomic distress. Specifically, a country's financial weakness has been consistently found to predict the lower tail of its GDP growth distribution. This line of research, pioneered by Giglio et al. (2016) and Adrian et al. (2018, 2019), introduced the concept of Growth-at-Risk (GaR), a term that parallels the Value-at-Risk (VaR) indicator widely employed in the financial industry.[1]

GaR has since gained traction among regulators worldwide and is now a key tool for central banks and financial supervisors in monitoring financial stability (see Prasad et al., 2019). This practice, which began as a domestic economy exercise aimed at predicting US real growth using the National Financial Conditions Index (NFCI),[2] has been promptly adopted by other countries (see Brownlees and Souza, 2021; Arrigoni et al., 2020).

In this study, we extend the existing literature on vulnerable growth by investigating how US financial conditions influence the conditional distribution of real credit growth in other countries. Building on the concept of vulnerable growth introduced by Adrian et al. (2019), we identify a credit growth channel for the transmission of global financial shocks, which we term *vulnerable funding*. Our findings reveal that US financial shocks have a larger, more significant impact on the lower quantiles of global real credit growth than they do on the central and upper quantiles.

These documented effects persist for up to three years after a US financial shock has occurred and can predict episodes of vulnerable growth worldwide. Results here emphasize the crucial role of lending in the international transmission of financial shocks to the real economy worldwide.

We also observe substantial cross-country heterogeneity in vulnerable funding. Countries with lower credit-to-GDP ratios and higher US investment relative to their GDP are more susceptible to US financial shocks. This result offers fresh insights that the extant literature (e.g., Alfaro et al., 2004; Kalemli-Özcan, 2019) do not provide, either because they do not consider as many countries as are considered here or because they do not focus specifically on macroeconomic scenarios where

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[1] See also the vulnerable growth literature, including Kiley (2021), Boyarchenko et al. (2019), Loria et al. (2019), Figueres and Jarociński (2020), and Delle Monache et al. (2023).

[2] The NFCI, calculated by the Chicago Fed, captures financial risk, leverage, and credit quality within a single indicator. It offers a comprehensive view of US financial conditions in money, debt and equity markets alongside both traditional and shadow banking systems.

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funding is vulnerable.

Our analysis uses the NFCI as an indicator of global financial conditions, recognizing the prominent role of the US, particularly its monetary policy, in shaping the commonality of global business and financial cycles (Ammer et al., 2018; Jordà et al., 2019; Miranda-Agrippino and Rey, 2020a, b; Bekaert et al., 2023). Nevertheless, our models also account for other global factors, both real and financial, which we extract from data on credit and real growth, and which may also influence global credit markets. The inclusion of these factors helps mitigate the endogeneity concerns extensively discussed in the domestic economy literature (see Plagborg-Møller et al., 2020; Reichlin et al., 2020). However, when domestic financial conditions are considered in our robustness checks, the impact of the NFCI generally remains negative and significant, particularly at the lower quantiles.[3]

The rest of this document is organized as follows: Section 2 outlines our methodology. Section 3 describes our data and sources. Sections 4 to 6 present the empirical results, and Section 7 concludes.

2. Empirical framework

To fully characterize the conditional distribution of future real credit growth as a function of current US financial conditions, we rely on quantile regressions (Koenker and Basset, 1978). For each country i, we estimate the following regression:

$$Q_\tau(y_{it+h}|\boldsymbol{X}_t) = \beta_{0i}(\tau) + \beta_{1i}(\tau)y_{it} + \beta_{2i}(\tau)nfci_t^{US} + \beta_{3i}(\tau)macro_t^{US} + \beta_{4i}(\tau)cross_t^g + \beta_{5i}(\tau)macro_t^g, \tag{1}$$

where y_{it+h} represents the quarterly change in real credit growth in logarithms for country i and forecasting horizon h, and $\boldsymbol{X}_t = (y_{it}, nfci_t^{US}, macro_t^{US}, cross_t^g, macro_t^g)$ is the set of predictors. The vector $\boldsymbol{\beta}(\boldsymbol{\tau}) = (\beta_{0i}(\tau), \beta_{i1}(\tau), \beta_{2i}(\tau), \beta_{3i}(\tau), \beta_{4i}(\tau), \beta_{5i}(\tau))'$ denotes a vector of parameters corresponding to the τ-th quantile.[4]

In what follows, we define the 5$^{\text{th}}$ quantile, $\tau = 0.05$, as Credit-at-Risk (CaR). Eq. 1 extends Adrian et al's. (2019) framework by considering other regressors in addition to lagged GDP growth and the domestic financial conditions index and, naturally, by modelling credit rather than GDP growth.

The key parameter is $\beta_{2i}(\tau)$, which captures the effect of US financial conditions ($nfci_t^{US}$) on the distribution of real credit growth in other countries. In a financially integrated world, US financial conditions reflect global risk and we would expect $\beta_{2i}(\tau)$ to be negative and statistically significant. Meanwhile, $\beta_{3i}(\tau)$ represents the effect of macroeconomic uncertainty in the US ($macro_t^{US}$) —proxied by the conditional volatility of industrial production growth—on the distribution of credit growth in other countries.

Disentangling macroeconomic risk from financial risk in the regression is recommended since the predictive power of financial indicators is significantly reduced when macroeconomic indicators are included in GaR equations (see Plagborg-Møller et al., 2020, and Reichlin et al., 2020). Naturally, this result could also apply when modeling credit growth as opposed to GDP growth.

In Eq. 1 we include two additional variables that control for the commonality of business and financial cycles across the globe. Coefficient $\beta_{4i}(\tau)$ captures the commonality of credit growth across the different countries ($cross_t^g$), while $\beta_{5i}(\tau)$ reflects the global macroeconomic uncertainty that is not driven by US financial conditions ($macro_t^g$). The inclusion of these factors draws inspiration from Chudik and Pesaran (2015) and Harding et al. (2020), who emphasize the importance of incorporating common factors when modelling the dynamics of the multiple cross-sectional units in international economics exercises so as to reduce the risk of omitting relevant confounders. In the following section, we provide further details on how these global factors are constructed.

Eq. (1) emphasizes the factor structure of our empirical framework. The model for each country is estimated using individual conditional quantile regressions as proposed by Koenker and Bassett (1978), but y_{it+h} in all countries is a function of $nfci_t^{US}$, $macro_t^{US}$, $cross_t^g$, and $macro_t^g$, which do not have cross-sectional variation yet vary over time.

All variables were normalized before estimation to have zero mean and unit variance. By so doing, we are able to compare the magnitude and sign of the effects across different countries: Hence, the higher the absolute value of these standardized coefficients, the stronger the effect.

Additionally, to compare our results with those in the literature on vulnerable growth, we estimate Eq. (1) using GDP growth as the dependent variable.

3. Data

We base our empirical framework on a large dataset that includes a set of macroeconomic and financial variables for advanced and emerging economies and US data on financial and macroeconomic risks.

Macro and financial data. We use the quarterly change in logarithms of real credit growth and real GDP growth. These variables are drawn from a long quarterly data panel constructed and provided by Monnet and Puy (2019), which covers real GDP, credit, consumer prices, nominal stock prices, and sovereign bond yields for advanced and emerging countries over the whole post-war period. Compared to similar sources, such as the Organization for Economic Cooperation and Development (OECD) or the Bank of International Settlements (BIS), the coverage gains for these data are around 20 to 30% for advanced economies, and more than 100% for emerging economies. Specifically, real GDP is available for 37 countries and real credit for 45 countries, with a sample size that ranges between 1950-Q1 and 2019-Q4 per country.[5] However, here we restrict the start of our sample to 1960-Q1 because of poor data quality in the earlier periods. Table A2 in the online appendix presents the definition of the variables considered in the analysis and Fig. A1 plots both the variables along with their associated unit root tests.[6]

US financial conditions. To measure US financial conditions we rely on the NFCI, which has been widely used in the GaR literature.[7] Following the seminal work of Adrian et al. (2019), the NFCI has become one of the most relevant predictors of the lower conditional quantiles of output growth for the US (see, for example, Arrigoni et al., 2020; Brownlees and Souza, 2021; Beutel et al., 2020). Based on Brave and Butters (2011), the NFCI is a weighted average of 105 measures of financial activity, each scaled to have zero mean and unit standard deviation. Positive NFCI values imply that US financial conditions are tighter than average. Since the NFCI has weekly periodicity, we aggregate it for our analysis by taking quarterly averages starting at 1971-Q1. This means that for our econometric estimation, the sample is reduced to around 200 quarterly observations.

US macroeconomic uncertainty. Drawing inspiration from the recent literature on real uncertainty (e.g., Jurado et al., 2015; Ludvigson et al., 2021), we consider a simple measure of real uncertainty in our empirical models. Specifically, we adopt the conditional variance of

[3] See Section 6.2. and online appendix I.

[4] Alternatively, Section 6.1. expands this specification by incorporating up to four lags of the dependent variable and Section 6.2. introduces a country-specific financial condition index. This was done to assess the robustness of our specification. The results are presented in online appendices H and I.

[5] See Table A1 in the online appendix for details on the data and Table A3 for summary statistics.

[6] We check for unit roots using the augmented Dickey-Fuller (ADF) test.

[7] The NFCI is constructed and published by the Federal Reserve Bank of Chicago and is available at: https://www.chicagofed.org/publications/nfci/index

industrial production growth, as proposed by Bekaert et al. (2022), using the Bad Environment-Good Environment framework developed in Bekaert and Engstrom (2017). We use quarterly averages of monthly values of the corresponding index.

Global factors. We consider two types of variable to proxy for global factors. The first is associated with the commonality of business and financial cycles, as previously emphasized in the literature. The central idea of our approach is to summarize fluctuations in the target dependent variable (output or credit growth) for a large, heterogeneous panel of advanced and emerging economies using a factor model. We estimate this common factor using a two-step procedure. In the first step, we employ principal component analysis (PCA) on the dependent variable.[8] In the second step, we use the Kalman filter to recursively compute the expected value of the common factor. This process is iterated until convergence of the expected maximization (EM) algorithm (Doz et al., 2012). This procedure is especially important for our work here, as we have to deal with a few missing data points for some countries (see online appendix A1). A comprehensive description and analysis of the global factors can be found in online appendix B.

Finally, the second global factor is related to world economic uncertainty, which is captured by the quarterly realized volatility of the monthly world industrial production (WPI) index, based on Baumeister and Hamilton (2019).[9]

Cross-country determinants. To assess cross-country heterogeneity, we construct three variables related to the size of financial markets, financial interconnectedness with the US, and the degree of capital account openness. We measure the size of credit markets by the annual average of the credit-to-GDP ratio for each country. These data have been collected from the World Bank database.[10] The degree of financial interconnectedness with the US is measured by the total US direct investment in the country as a percentage of the country's GDP, and the degree of capital account openness by the Chinn-Ito index, which measures the country's intensity of capital controls (Chinn and Ito, 2006). For the former, we use historical data on US direct investment abroad drawn from the National Bureau of Economic Research and nominal GDP taken from International Monetary Fund statistics.[11] For the latter, we use information publicly available at the authors' website.[12] For each of these indicators, we compute the country's average value (see online appendix A4 for details of these calculations).

4. Results

Although our key contribution is to examine how US financial conditions affect credit growth in other countries, it is interesting to note just how similar vulnerable funding and vulnerable growth are, with both emerging from the same conceptual framework developed by Adrian et al. (2019). For this reason, in what follows, we begin by analyzing the effects of US financial conditions on the conditional distribution of real credit growth and real GDP growth in other countries. Subsequently, we examine the relationship between these two indicators.

4.1. Vulnerable funding

We begin, therefore, by examining the impact of US (global) financial shocks on real credit growth.[13] We run three different regressions for each of the 45 countries in our sample and for forecasting horizons $h = \{0, 1, 4\}$. In online appendix C, we extend the analysis for longer forecasting horizons, specifically $h = \{8, 12\}$. All specifications control for US macroeconomic uncertainty and the two global factors as indicated in Eq. 1.

Table 1 summarizes the results for quantiles $\tau = \{0.05,\ 0.25, 0.5, 0.75, 0.95\}$ and for forecasting horizons $h = \{0, 1, 4\}$. More specifically, the table reports the following information: the first and last quartiles of the distribution of estimated coefficients—namely the IQR, the proportion of countries for which the variable is statistically significant at a 90% confidence level (Sig.), and the average percentage improvement of the tick loss (TL) obtained by adding the NFCI to the respective model (ΔTL).

We observe that, in general, the impact of the NFCI on real credit growth is more frequently negative at the lower quantiles than at the central and higher quantiles of real credit growth, irrespective of the forecasting horizon. This result suggests that global financial fragility, as proxied by US financial fragility, is a relevant predictor of downside risks to real credit growth in the global economy.

Indeed, in Table 1, we observe that the percentage of countries for which the impact of NFCI is significant at $\tau = 0.05$, is around 39% for $h = 1$ (out of 45 countries). The IQR indicates that these effects are mostly negative.[14] The effect peaks for $h = \{12\}$ (see online appendix C). This shows that the global economy requires up to three years to face the repercussions of the transmission of most of the NFCI shocks to the global credit market, which is consistent with a credit view explanation of the transmission of shocks, i.e., the deterioration of financial conditions seems to generate a reduction in international funding sources for financing domestic investment.

Second, we observe that both US macroeconomic uncertainty and global factors significantly predict fluctuations in real credit growth across all quantiles. However, these variables impact real credit growth around the world heterogeneously. Furthermore, by incorporating the NFCI into the regression, the most substantial average improvement is observed at the lowest quantile and for the one-year-ahead forecasting horizon, with an improvement of 3.07 percentage points (see ΔTL in Table 1).

It is noteworthy that the effects on credit exhibit considerable heterogeneity across countries. Specifically, while a substantial proportion of countries presents a negative response to a deterioration in financial conditions in the US, another set of countries does not react or even exhibits a positive response to the shock. In Section 5, we provide an explanation for this heterogeneity by conducting a cross-section analysis.

4.2. Vulnerable growth

Table 2 summarizes the estimation results for real GDP growth as the dependent variable in Eq. (1) for quantiles $\tau = \{0.05, 0.25, 0.5, 0.75, 0.95\}$ and for forecasting horizons $h = \{0, 1, 4\}$, respectively.[15] All specifications control for US macroeconomic

[8] In the first stage of the PCA, we initially trimmed the data by removing values outside the 5th and 95th percentiles to mitigate the impact of outliers on our estimates. Subsequently, missing values were imputed using the respective country-specific variable averages.

[9] The WPI index can be found on one of the author's websites: https://sites.google.com/site/cjsbaumeister/datasets.

[10] Credit refers to financial resources (loans, securities, and other claims) provided to the private sector by banks. Market capitalization is the share price times the number of shares outstanding for listed domestic companies.

[11] See Table A4 in the online appendix for information on these variables.

[12] Available at https://web.pdx.edu/~ito/Chinn-Ito_website.htm.

[13] Credit and equity are the two main funding sources used by corporations to finance their operations, especially their investments (Parsons and Titman, 2008; Fama and French, 2012). In online appendix E, we show that our main results also hold for stock markets.

[14] The effects are quantitatively large. For instance, the largest negative effects for $h = \{0, 1, 4\}$, are -0.29, -0.42 and -0.44, respectively. This implies that a one standard deviation increase in NFCI is associated with a decrease of 0.38 standard deviation in the conditional quantile of standardized credit growth.

[15] In online appendix D we extend the analysis to longer horizons, $h = \{8, 12\}$.

Table 1
Quantile regressions, Impact on real credit growth

		q=0.05	q=0.25	q=0.50	q=0.75	q=0.95
a. Contemporaneous (h=0)						
$nfci_t^{US}$	IQR	[-0.29;0.16]	[-0.10;0.07]	[-0.05;0.17]	[0.00;0.23]	[-0.09;0.36]
	Sig.	0.23	0.11	0.23	0.34	0.20
$macro_t^{US}$	IQR	[-0.18;0.16]	[-0.09;0.07]	[-0.06;0.03]	[-0.10;0.03]	[-0.21;0.12]
	Sig.	0.23	0.02	0.02	0.09	0.14
$cross_t^G$	IQR	[-0.59;-0.06]	[-0.39;-0.11]	[-0.49;-0.15]	[-0.6;-0.18]	[-0.78;-0.27]
	Sig.	0.48	0.55	0.77	0.77	0.70
$macro_t^G$	IQR	[-0.20;0.13]	[-0.13;0.09]	[-0.13;0.07]	[-0.15;0.04]	[-0.19;0.09]
	Sig.	0.25	0.18	0.23	0.30	0.16
b. One-quarter-ahead (h=1)						
y_{it}	IQR	[0.06;0.35]	[0.09;0.38]	[0.10;0.41]	[0.07;0.42]	[0.05;0.40]
	Sig.	0.36	0.61	0.73	0.66	0.41
$nfci_t^{US}$	IQR	[-0.42;0.13]	[-0.19;0.02]	[-0.02;0.12]	[0.03;0.20]	[-0.01;0.36]
	Sig.	0.39	0.23	0.14	0.23	0.23
$macro_t^{US}$	IQR	[-0.15;0.20]	[-0.08;0.03]	[-0.11;0.01]	[-0.15;-0.04]	[-0.24;0.01]
	Sig.	0.27	0.07	0.07	0.09	0.18
$cross_t^G$	IQR	[-0.15;0.37]	[-0.09;0.15]	[-0.10;0.11]	[-0.18;0.06]	[-0.36;0.10]
	Sig.	0.41	0.43	0.36	0.34	0.3
$macro_t^G$	IQR	[-0.18;0.11]	[-0.10;0.05]	[-0.10;0.03]	[-0.11;0.04]	[-0.19;0.16]
	Sig.	0.14	0.09	0.14	0.14	0.2
c. Four-quarter-ahead (h=4)						
y_{it}	IQR	[0.20;0.55]	[0.27;0.52]	[0.29;0.53]	[0.29;0.53]	[0.24;0.43]
	Sig.	0.57	0.82	0.91	0.77	0.59
$nfci_t^{US}$	IQR	[-0.44;0.04]	[-0.18;0.07]	[-0.06;0.06]	[0.00;0.15]	[-0.09;0.18]
	Sig.	0.20	0.25	0.14	0.18	0.14
$macro_t^{US}$	IQR	[-0.07;0.19]	[-0.09;0.05]	[-0.07;0.05]	[-0.10;0.04]	[-0.12;0.17]
	Sig.	0.20	0.14	0.07	0.07	0.16
$cross_t^G$	IQR	[-0.22;0.12]	[-0.13;0.03]	[-0.17;-0.05]	[-0.25;-0.05]	[-0.40;-0.08]
	Sig.	0.30	0.20	0.34	0.39	0.43
$macro_t^G$	IQR	[-0.23;0.09]	[-0.10;0.02]	[-0.08;0.02]	[-0.11;0.07]	[-0.15;0.21]
	Sig.	0.14	0.07	0.11	0.07	0.23
d. Average improvement of the TL by adding the NFCI						
h=0	ΔTL	2.73	1.00	1.23	1.99	2.42
h=1	ΔTL	2.90	0.69	0.51	1.27	2.51
h=4	ΔTL	3.07	1.19	0.58	0.97	2.37

Note: Sig. denotes the proportion of countries for which the variable is statistically significant at 90% confidence level; IQR shows the first and third quartiles of the estimated coefficients; ΔTL shows the average improvement (in percentage terms) of the tick loss obtained by adding the NFCI to the respective model. Intercepts are omitted from the table. Standard errors are based on a block bootstrapping with four blocks and 500 replications (Gregory et al., 2018). Sample: 1971Q1 to 2019Q4 for 45 countries: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Cyprus, Denmark, Finland, France, Germany, Greece, Guatemala, Honduras, Iceland, India, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and Uruguay.

uncertainty and two global factors. Again, the table reports the following information: the first and last quartiles of the distribution of estimated coefficients, specifically the interquartile range (IQR), the proportion of countries for which the variable is statistically significant at a 90% confidence level (Sig.), and the average percentage improvement in TL obtained by incorporating the NFCI into the respective model (ΔTL).

Two main findings emerge from the analysis. First, the impact of the NFCI on real GDP growth tends to be more frequently negative and statistically significant at the lower quantiles of GDP than at the central and higher quantiles. This result suggests that US financial fragility is an important predictor of downside risks to real GDP growth in the global economy, providing further evidence of GaR predictability for a relatively large set of countries (as noted previously by Brownlees and Souza, 2021, and Arrigoni et al., 2020, among others). In particular, the percentage of countries for which the impact of NFCI on the quantile at $\tau = 0.05$ is statistically significant increases from 25% (out of 36 countries) when $h = 0$ to 33% when $h = 4$. The interquartile range is sizable, particularly with the first and third quartiles registering negative values in the latter forecasting horizon. These effects remain significant for higher forecasting horizons (see online appendix D).

Second, US macroeconomic uncertainty and global factors heterogeneously explain real GDP growth across different quantiles and countries. The impact of US macroeconomic uncertainty is primarily observed at the lower quantiles and contemporaneously, while its effects diminish for longer horizons. The cross-sectional factor is highly significant, aligning with the documented commonality of business and financial cycles worldwide (Ammer et al., 2018; Jordà et al., 2019; Miranda-Agrippino and Rey, 2020a, b). We observe that this global factor has heterogeneous impacts on real activity around the world.

The coefficients of these global factors encompass a wide range of values, often exhibiting high negative values, particularly at the lowest quantiles. While higher values of US macroeconomic uncertainty reflect higher macroeconomic uncertainty, the interpretation of this cross-sectional factor is not immediate, as it captures the cross-correlation between countries. Taken together, these results suggest the association of global macroeconomic conditions with real GDP growth. As regards the TL gain, with the addition of the NFCI to the regression, the most significant average improvement is observed at the lowest quantile and the one-year-ahead forecasting horizon, resulting in a gain of 3.43 percentage points (see ΔTL in Table 2).

4.3. The link between vulnerable funding and vulnerable growth

Here, we examine the connection between our estimates of vulnerable funding and vulnerable growth. Specifically, we address the question as to whether vulnerable funding predicts vulnerable growth in the time-series dimension. To do so, we first estimate the predictive 5% conditional quantile across countries using Eq. (1) and each forecasting horizon for real GDP growth and real credit growth, respectively. In the

Table 2
Quantile regressions, Impact on real GDP growth

		q=0.05	q=0.25	q=0.50	q=0.75	q=0.95
a. Contemporaneous (h=0)						
$nfci_t^{US}$	IQR	[-0.30;0.00]	[-0.13;0.08]	[-0.08;0.09]	[0.01;0.13]	[-0.10;0.21]
	Sig.	0.25	0.25	0.17	0.22	0.25
$macro_t^{US}$	IQR	[-0.34;0.17]	[-0.18;0.07]	[-0.09;0.07]	[-0.07;0.07]	[-0.05;0.17]
	Sig.	0.33	0.25	0.17	0.08	0.11
$cross_t^G$	IQR	[-0.48;0.01]	[-0.51;-0.11]	[-0.52;-0.20]	[-0.56;-0.22]	[-0.68;-0.27]
	Sig.	0.44	0.64	0.78	0.83	0.67
$macro_t^G$	IQR	[-0.24;0.11]	[-0.09;0.05]	[-0.06;0.02]	[-0.06;0.02]	[-0.13;0.08]
	Sig.	0.17	0.11	0.06	0.08	0.17
b. One-quarter-ahead (h=1)						
y_{it}	IQR	[-0.25;0.16]	[-0.13;0.21]	[-0.1;0.23]	[-0.17;0.16]	[-0.33;-0.03]
	Sig.	0.31	0.39	0.47	0.33	0.42
$nfci_t^{US}$	IQR	[-0.29;0.15]	[-0.11;0.01]	[-0.05;0.10]	[-0.03;0.14]	[-0.02;0.33]
	Sig.	0.25	0.17	0.14	0.25	0.22
$macro_t^{US}$	IQR	[-0.45;-0.02]	[-0.19;0.02]	[-0.13;0.00]	[-0.12;0.04]	[-0.14;0.25]
	Sig.	0.25	0.17	0.14	0.08	0.22
$cross_t^G$	IQR	[-0.34;0.16]	[-0.32;0.00]	[-0.36;-0.07]	[-0.4;-0.09]	[-0.54;-0.27]
	Sig.	0.28	0.44	0.50	0.67	0.50
$macro_t^G$	IQR	[-0.20;0.06]	[-0.10;0.04]	[-0.08;0.02]	[-0.05;0.06]	[-0.09;0.18]
	Sig.	0.22	0.11	0.06	0.11	0.28
c. Four-quarter-ahead (h=4)						
y_{it}	IQR	[-0.21;0.19]	[-0.12;0.06]	[-0.11;0.08]	[-0.12;0.06]	[-0.23;0.02]
	Sig.	0.36	0.25	0.22	0.22	0.17
$nfci_t^{US}$	IQR	[-0.53;-0.03]	[-0.2;-0.03]	[-0.08;0.05]	[-0.02;0.09]	[-0.1;0.27]
	Sig.	0.33	0.28	0.08	0.17	0.19
$macro_t^{US}$	IQR	[-0.09;0.16]	[-0.02;0.09]	[-0.03;0.10]	[-0.04;0.15]	[-0.02;0.31]
	Sig.	0.06	0.14	0.08	0.14	0.22
$cross_t^G$	IQR	[-0.08;0.41]	[-0.09;0.13]	[-0.15;0.05]	[-0.16;-0.01]	[-0.38;-0.08]
	Sig.	0.28	0.22	0.19	0.22	0.39
$macro_t^G$	IQR	[-0.15;0.16]	[-0.09;0.05]	[-0.05;0.06]	[-0.02;0.05]	[-0.11;0.12]
	Sig.	0.25	0.11	0.00	0.06	0.14
d. Average improvement of the TL by adding the NFCI						
h=0	ΔTL	2.12	1.17	0.86	1.34	2.82
h=1	ΔTL	2.38	0.87	0.61	1.07	1.99
h=4	ΔTL	3.43	1.58	0.57	0.71	2.03

Note: Sig. denotes the proportion of countries for which the variable is statistically significant at 90% confidence level; IQR shows the first and third quartiles of the estimated coefficients; ΔTL shows the average improvement (in percentage terms) of the tick loss obtained by adding the NFCI to the respective model. Intercepts are omitted from the table. Standard errors are based on a block bootstrapping with four blocks and 500 replications (Gregory et al., 2018). Sample: 1971Q1 to 2019Q4 for 36 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Iceland, India, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Philippines, Portugal, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, and Uruguay.

case of real GDP growth, this estimate resembles the GaR measure commonly employed in the literature (see Adrian et al., 2019). Second, we run regressions by pooled ordinary least squares using the h-step-ahead GaR estimates as the dependent variable and the current GaR and CaR estimates as independent variables. We use robust Newey and West (1987) standard errors.

Our linear regressions across various forecasting horizons reveal a robust connection between GaR and CaR. Table 3 presents the regression results, depicting the predicted GaR at time $t + h$ as a function of the CaR and GaR estimates at time t. We observe that downside risks in credit growth play an essential role in anticipating future distress scenarios in output growth. This association is particularly pronounced on the one-quarter-ahead horizon, demonstrating an explanatory power of approximately 58% (see column 1). This connection has substantial implications for policymakers, implying that after periods of vulnerable funding, they should also expect periods of vulnerable growth.

Additionally, in Fig. 1 we plot the GaR estimate at time $t + 1$ as a function of both GaR and CaR at time t, revealing a compelling positive correlation in both cases.

Table 3
Explaining GaR estimates for different horizons

	Dependent variable			
	GaR(t+1) (1)	GaR(t+4) (2)	GaR(t+8) (3)	GaR(t+12) (4)
CaR(t)	0.049***	-0.007	0.067***	0.024
	(0.012)	(0.019)	(0.018)	(0.016)
GaR(t)	0.790***	0.342***	0.153***	0.146***
	(0.014)	(0.021)	(0.018)	(0.017)
Constant	-0.241***	-0.998***	-1.130***	-1.174***
	(0.023)	(0.031)	(0.031)	(0.025)
Observations	6,539	6,440	6,300	6,160
R^2	0.584	0.121	0.042	0.037
Adjusted R^2	0.584	0.121	0.041	0.036

Note: Significance level *p<0.10**p<0.05***p<0.01. Newey and West (1987) standard errors are used.

5. Determinants of vulnerable funding

5.1. Graphical analysis

In this subsection, we visually examine the primary drivers of vulnerable funding at the country level. We link our results with three classical determinants of the international spread of financial shocks: the size of credit markets, the relative importance of US foreign investment for each country, and the Chinn-Ito index of financial openness.

Fig. 2 shows the results for different forecasting horizons, the countries ordered according to the measure that provides the clearest pattern (credit-to-GDP ratio). We observe that negative effects tend to be concentrated in the left tail of the distribution of credit for all countries, and that they tend to be larger in absolute value and negative for those

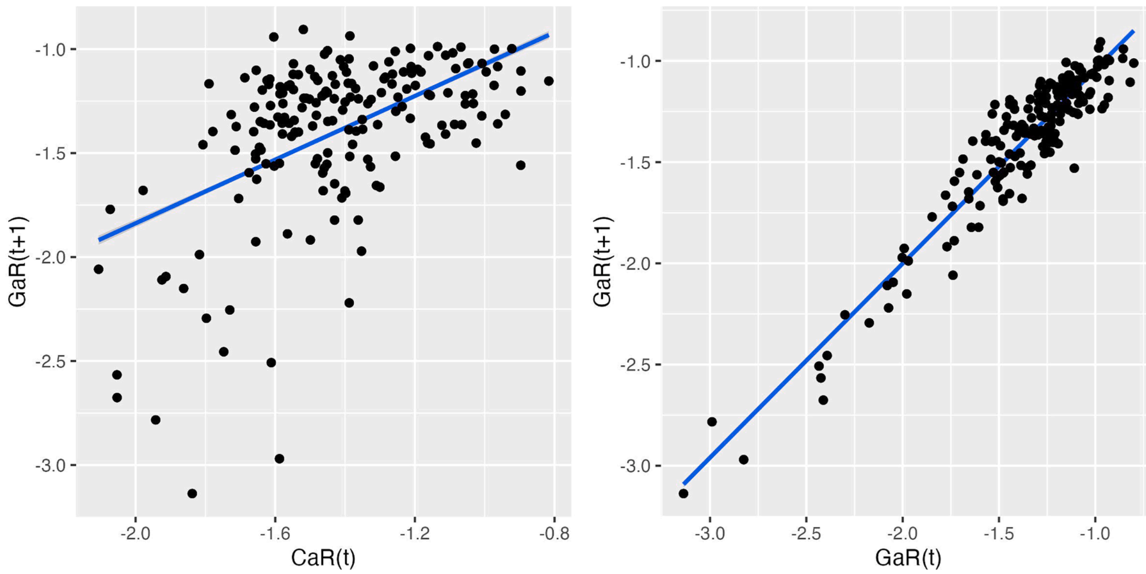

Fig. 1. Relationship between GaR and CaR at the one-quarter-ahead horizon.
Note: Each point represents the cross-sectional mean at each point in time.

countries at the bottom of the figure, i.e., those with a lower credit-to-GDP ratio. That is, in general, the smaller the credit market, the more likely it is that the country will experience vulnerable funding episodes as a result of a tightening in US financial conditions.

The size of the credit market is associated with market development and, therefore, our findings highlight the asymmetric impact of NFCI shocks on both emerging and advanced economies. This is in line with the findings of Alfaro et al. (2004) and Kalemli-Özcan (2019).[16]

In online appendix F (Figs. F1 and F2), we present additional results that sort the countries by their degree of financial interconnectedness with the US and by the Chinn-Ito index of financial openness. Again, negative responses are found at the lower quantiles for the first of these two indexes, especially at the top of the figure. This suggests that economies with high US investment relative to their GDP are more sensitive to NFCI shocks.

5.2. *Cross-sectional regressions*

In this subsection, we present the results of exploratory regressions examining the relationship between vulnerable funding and the three key determinants of the international propagation of financial shocks. The dependent variables in our regressions are the slope coefficients of NFCI on real credit growth at various quantiles, while the independent variables include the ratio of US direct investment to each country's GDP, the credit-to-GDP ratio and the Chinn-Ito index for each country. The indicators are averaged across the sample period (1960 Q1 – 2019 Q4).

The results in Table 4 show that when $h = \{0, 4, 8, 12\}$, market size significantly explains the transmission of NFCI shocks at the lowest quantile. This is in line with theoretical expectations and corroborates findings from previous studies, suggesting that the larger the market the lower the negative effect of US financial conditions is on that market. Additionally, financial closeness to the US helps explain the lowest quantiles when $h = \{8, 12\}$. Greater financial ties to the US correspond to increased vulnerability to US financial shocks.

6. Robustness checks

6.1. *Controlling for additional lags of the dependent variable*

In online appendix H, we include additional lags of the response variable in our regressions. Specifically, we extend the baseline regressions (see Section 2) by adding up to four lags of the dependent variable for forecasting horizons $h = \{1, 4, 8, 12\}$. Overall, the results remain consistent in terms of the magnitude of the effects and their persistence across different forecasting horizons.

6.2. *Including country-specific financial indicators*

To examine the robustness of our findings while accounting for each country's financial conditions, we conduct an additional analysis in online appendix I. In this analysis, we expand our baseline regression (as described in Section 2) by incorporating a country-specific financial condition index (FCI) for a subset of countries. The FCI used is based on the methodology proposed by Koop and Korobilis (2014).

By integrating this database with our own data, we are able to create a sample comprising 21 countries. It is worth noting that this database resembles that employed in Brownlees and Souza's (2021) study, where it was used for an out-of-sample backtesting exercise involving GaR predictions for 24 OECD countries.

We observe that the FCI for each country exhibits a substantial and predominantly negative effect, which is often statistically significant, across various forecasting horizons and quantiles. However, it is notable that despite the inclusion of the FCI, the coefficients for the NFCI generally remain negative and significant. This is particularly evident at the lower quantiles.

[16] To investigate the role of macroprudential policies in attenuating episodes of vulnerable funding, we examine the case of Latin American and Caribbean (LAC) countries (see online appendix G) in two distinct periods: 2001–2008 and 2009–2019. During this second period, LAC countries implemented various macroprudential policies to stabilize credit growth and safeguard their financial stability against international financial shocks (Jara et al., 2009; Tovar et al., 2012; Gambacorta and Murcia, 2020; Giraldo et al., 2023). Our results, however, hold for both periods, indicating that macroprudential policies have not played a prominent role in reducing vulnerable funding in the region. Nevertheless, it should be noted that this is a correlational analysis that does not control for other factors at play and, as such, the outcome requires further examination.

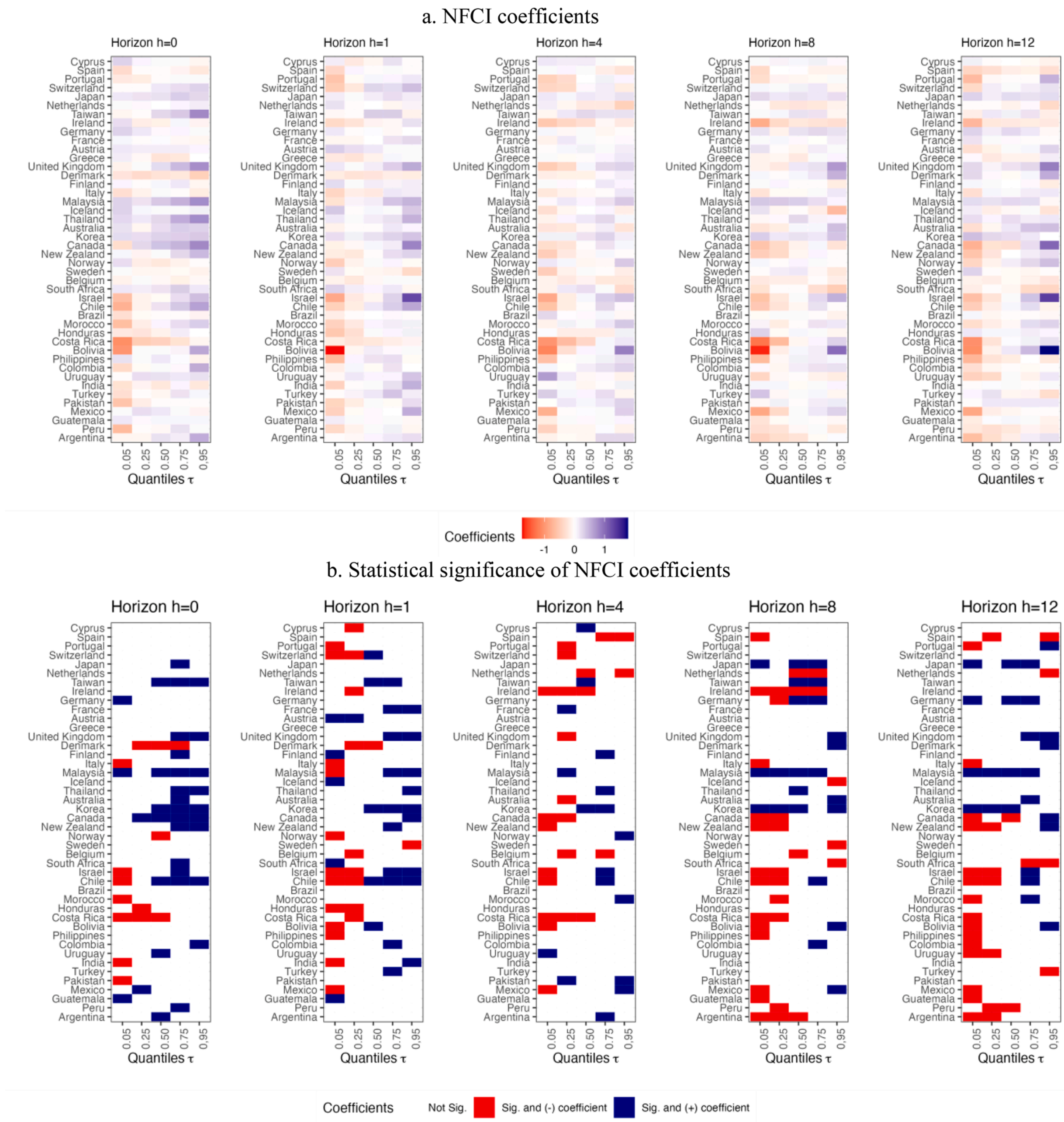

Fig. 2. NFCI impact on credit markets (CaR) for different forecasting horizons (countries listed in descending order by credit-to-GDP ratio.
Note: Panel A shows the standardized NFCI coefficients for $\tau = \{0.05, 0.25, 0.5, 0.75, 0.95\}$, different forecasting horizons, and 45 countries. Panel B shows the statistical significance of NFCI coefficients. The red (blue) shaded areas are defined as being negatively (positively) statistically significant at the 90% level of confidence, whereas the white shaded area corresponds to insignificant coefficients associated with the NFCI. The higher the absolute value of the beta coefficient, the stronger is the effect. Standard errors are based on a block bootstrapping with four blocks and 500 replications.

7. Conclusions

Our analysis provides the first systematic evidence of vulnerable funding episodes in the global economy. Specifically, we find that US financial shocks possess significant predictive power at the lowest quantiles of credit growth across a large set of countries. However, these effects exhibit considerable heterogeneity across different dimensions.

Our methodology adopts quantile regressions, in line with the focus taken by the GaR literature. To enrich our model specification, we incorporate global economic and financial factors, leveraging a comprehensive dataset covering 45 countries, with information spanning nearly six decades.

We also identify two classical determinants of the international spread of financial shocks – namely, market size and financial closeness to the US – as key factors influencing vulnerable funding at different forecasting horizons. Our results indicate that markets with lower credit-to-GDP ratios and higher levels of US investment relative to the country's GDP are more susceptible to US financial shocks.

Our results suggest that US financial conditions serve as a predictive indicator of future vulnerability in domestic credit markets. Hence, we provide evidence that international funding markets act as a source of persistence and amplification for financial shocks originating from the global economy.

These findings underscore the critical role played by funding in transmitting recessionary shocks across the world. They also highlight the importance of monitoring funding variables and their relationship

Table 4
Cross-sectional determinants of the slope coefficients of NFCI on real credit growth at different quantiles

Horizon	Variable	q=0.05	q=0.25	q=0.50	q=0.75	q=0.95
0	Constant	-0.361***	-0.049	0.025	0.117***	0.213**
	US inv./GDP (%)	-0.001	-0.002	-0.001	0.001	0.002
	Credit/GDP (%)	0.004**	0.000	0.000	0.000	-0.001
	Chinn-Ito index	0.025	0.025	0.023	0.010	0.029
1	Constant	-0.35***	-0.046	0.043	0.101***	0.219**
	US inv./GDP (%)	-0.002	-0.003	-0.001	-0.003	0.005
	Credit/GDP (%)	0.002	0.000	0.000	0.001	-0.001
	Chinn-Ito index	0.014	0.005	0.008	-0.022	-0.001
4	Constant	-0.307**	-0.068	-0.032	0.109***	0.214***
	US inv./GDP (%)	-0.006	-0.007**	-0.006***	-0.002	-0.008***
	Credit/GDP (%)	0.003*	0.001	0.001***	0.000	-0.001
	Chinn-Ito index	-0.055	-0.039**	-0.013	-0.022	0.011
8	Constant	-0.379**	-0.176***	0.003	0.085**	0.123
	US inv./GDP (%)	-0.011*	-0.008***	-0.006***	-0.006***	-0.005**
	Credit/GDP (%)	0.004**	0.002***	0.001	0.000	-0.001
	Chinn-Ito index	-0.044	-0.025	0.015	0.029	0.043
12	Constant	-0.387***	-0.132**	-0.004	0.106**	0.258*
	US inv./GDP (%)	-0.009*	-0.003	-0.005***	-0.002	-0.005
	Credit/GDP (%)	0.004**	0.001*	0.000	-0.001	-0.002
	Chinn-Ito index	-0.034	-0.009	0.015	0.044*	0.126**

Note: Significance level based on robust standard errors: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. NFCI coefficients are drawn from the baseline model which additionally controls for one lag of the dependent variable and the macroeconomic and financial global factors. Sample of 45 countries: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Cyprus, Denmark, Finland, France, Germany, Greece, Guatemala, Honduras, Iceland, India, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and Uruguay.

with global financial shocks in regular financial stability assessments conducted by central banks and regulators worldwide.

A deterioration in US financial conditions warrants policy actions in other economies. For example, worsening financial conditions, which are associated with reduced global liquidity and credit availability, can exacerbate the decline in investment and impede economic recovery following an international shock. In such scenarios, domestic fiscal and monetary authorities play a crucial role in stimulating internal demand by reducing financing costs and providing liquidity to businesses that seek to invest.

Our study reveals that this policy approach holds broader applicability than previously acknowledged in the literature. The deterioration in funding opportunities, whether in credit or stock markets, is observed, albeit to varying degrees, across all types of economies.

CRediT authorship contribution statement

Helena Chuliá: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ignacio Garrón:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jorge M. Uribe:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2024.107314.

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