"Vulnerable Funding in the Global Economy"

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Abstract

We study the international propagation of financial conditions from the United States to global financial markets. The impact is highly heterogeneous alongside the quantiles of the distribution of the two major funding sources, credit and equity. Indeed, it is greater on the lower quantiles, which means that analogous to vulnerable growth episodes, examined by the past literature, there exist as well vulnerable funding periods of a global scale, originated from financial weakness in the US. These episodes are related to downside risk in terms of credit creation and firms' market value around the world. Our estimates differentiate between first and second moment (i.e. uncertainty) shocks to financial conditions. This distinction proves to be relevant as it uncovers a complex propagation of shocks via different economic channels. On the one hand, credit growth largely responds to first moment shocks of US financial conditions four quarters after their occurrence, which is consistent with a credit view explanation of the transmission. On the other hand, stock markets react more sensitively and rapidly (mainly within a quarter) to second moment shocks, which can be theoretically associated with a portfolio channel underlying the shocks spread. We also document a heterogeneous impact across countries. In the case of credit growth this heterogeneity is better explained by the size or depth of the markets, while in the case of stock markets, the explanation is rooted on the strength of the financial connectedness with the US.

JEL classification: E44, F34, F37, F44, G15.

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1. Introduction

An influential group of recent studies has documented significant predictive power of financial conditions on real economic activity during distressed macroeconomic scenarios, that is, on the left (and negative) tail of the GDP growth distribution. This literature, pioneered by the works of Giglio et al. (2016) and Adrian et al. (2018, 2019) has coined the term *Growth at Risk* (GaR), which echoes the concept of Value at Risk, widely used and understood by regulators and practitioners everywhere for at least two decades[1]. In fact, the indicator has gained popularity among international regulators to the point of becoming part of the toolkit of central banks and financial supervisors available to monitor financial stability. Hence, estimating and reporting the lowest quantiles of the GDP distribution, predicted by financial conditions, one or several quarters ahead, has become standard practice (Prasad et al., 2019). This practice, which originated as a domestic economy exercise, in which the aim was to predict the GDP of the US with an index of financial conditions of the same country, usually the National Financial Conditions Index (NFCI)[2], quickly became global in nature, so the ability of financial conditions to predict the left tail of economic activity in a relatively large set of different countries has been examined and evaluated as well (e.g. Brownlees and Souza, 2020; Arrigoni et al. 2020).

We contribute to this literature in three ways. i) First, unlike previous studies that examine the effect of financial conditions on international real economic activity, we focus on a crucial intermediate step: We study how financial conditions in the US impact funding markets (credit and stocks) on a large set of countries around the world, under macro-financial distress scenarios. In other words, we focus on *vulnerable funding* instead of *vulnerable growth*. This intermediate step is crucial because financial shocks do not transit directly, or in a vacuum, from the US to the global economic activity. On the contrary, US financial conditions mainly impact global economic activity by deteriorating funding opportunities for households and firms around the world. This distinction is also important from a policy perspective, because it is at this intermediate financial level where policies that seek to safeguard the financial stability

[1] See as well on the vulnerable growth literature the works by Kiley (2018), Boyarchenko et al. (2019), Loria et al. (2019), Figueres and Jarociński (2020), and Delle Monache et al. (2020).

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

of domestic economies can expect to exert some type of mitigation of the adverse effects of the large and negative financial shocks that may emerge from the United States market. In this respect we document a larger and more significant impact of US Financial conditions on the lowest quantiles of credit and stock prices on a global scale than on the central quantiles. ii) Second, also unlike the previous literature, we acknowledge that financial conditions must be understood in a broader sense that includes not only changes in *the first moment* of financial conditions (as measured by the NFCI) but also changes in the *second moment* of financial conditions (which are better approximated by the index of financial uncertainty proposed by Ludvigson et al. (2021)). First and second moment shocks impact in dissimilar ways global funding. On the one hand, credit growth largely responds to first moment shocks in US financial conditions four quarters after their origination, which is consistent with a reduction of international funding sources for financing domestic investment, and therefore with the *international credit view* for the transmission of financial shocks across different countries. On the other hand, stock markets react more sensitively and rapidly (mainly within a quarter) to second moment shocks. This latter effect is more consistent with an expectations channel of the transmission of shocks, which in turn is associated with likely *portfolio* rebalancing by international portfolio holders, following an increase of US financial uncertainty. We empirically show that both channels, the *credit view* and the *portfolio view* are complementary, and both are necessary to understand how financial conditions in the US spillover to the rest of the world. iii) Third, we examine what is the most likely reason for a given country's vulnerability to changes in the financial conditions of the US. Namely, we test whether such vulnerability can be explained by the size or depth of a country's financial market, as it can be inferred from previous studies (e.g., Alfaro et al., 2004; Kalemli-Özcan, 2019), or if the explanation is rooted on the strength of the financial connectedness of a given country with the US. We show that the answer depends on whether we focus on credit or stock markets. In the case of credit markets, the most persistent and negative outcomes in terms of vulnerability are clearly more associated with the size or depth of the market while, in the case of stock markets, vulnerable funding episodes are associated with financial closeness to the US. This result sheds new lights on the problem compared to the previous literature, which does not employ the large number of countries that we consider, and also does not focus on the macro-financially distressed scenarios when funding is vulnerable.

To achieve our objectives we analyze vulnerable funding around the world. Vulnerable funding consists of two indicators: *Credit at Risk* (CaR) and *Equity at Risk* (EaR). The former refers to the impact of financial conditions of the US (including financial uncertainty) on the lowest quantiles of real credit growth and the second, on the lowest quantiles of the stock market prices. Loans and shares are the two main funding sources used by corporations to finance their operations, especially their investment (Parson and Titman, 2008; Fama and French, 2012). Therefore, evaluating the impact of financial conditions of the world's largest economy, on the lowest quantiles of the growth of credit and stock prices of the rest of the world is a crucial gap in the literature that we aim to remedy. Our approach intends to be comprehensive, thus we include more than 40 countries in our estimations, with information spanning six decades (from 1960 to 2019) in most of the cases. Our data set consists of economies in all stages of development and comprises all sorts of recessionary and non-recessionary periods. To the best of our knowledge no previous article within the vulnerable growth literature has relied on such a large data set to back-up its claims.

Methodologically speaking, thanks to the multinational point of view that we adopt, we are able to circumvent two controversial issues regarding the identification of the estimated effects in the vulnerable growth literature. The first one related to the lack of relevant controls on economic activity, required to assess the causal effect of financial conditions on future growth, and the second related to the presence of global macroeconomic and financial cycles which need to be considered when one estimates the propagation of shocks on a global scale. Regarding the former Reichlin et al. (2020) and Plagborg-Møller et al. (2020) emphasize that the predictive power of financial conditions seems to disappear once the model controls for (enough) real-economy variables. Therefore, the deterioration of financial conditions might be more of an endogenous response of the system than of an exogenous shock that deteriorates future real economic activity. In other words, by lacking enough controls on real variables, the vulnerable growth literature might be overstating the true impact of financial conditions on future economic activity. Nevertheless, recent proposals by Reichlin et al. (2020), Plagborg-Møller et al. (2020), and the Adjusted-NFCI provided by the Chicago's Fed on its web site, all of which seek to isolate the dynamics of financial variables from the dynamics of real economic variables, before estimating financial conditions, are not free of criticisms either. In short, if unobservable financial conditions are defined as a factor conditioned on the previous estimation of a main economic activity component (i.e. basically the effect of financial conditions reduces to a residual of the unexplained variation of real economic variables), we are implicitly assuming in the estimation of the financial factor, that the real and financial sides of the economy can be in fact pristinely separated in such a way. Thus, the identification issue is translated from the estimation of the impact to the construction of the financial conditions factor, but the main controversy remains unsolved, whether the financial shock is an endogenous response of the system or an exogenous shock, presumably with effective forecasting power. This identification issue is related to the problem of identifying the effects of real and financial uncertainty on the real economy (Ludvigson et al., 2021; Carriero et al., 2020), and also to the long-winded controversy in the macroeconomics literature that revolves about the extent to which we can isolate the effects of policy variables, like the interest rate, on the real economy series[3].

Our identification assumption is less controversial, owing to the fact that we do not assume any behavior about real or financial variables in our model. Instead, we assume that the US financial conditions are exogenous to the domestic economy series included in our data set. That is, that the US is the origin of financial shocks and not the other way around. Indeed, this assumption is backed-up by recent literature that documents the dominant role of the US economy relative to other countries, and in particular its monetary policy, which significantly influences the commonality of business and financial cycles around the world (Ammer et al., 2018; Jordà et al., 2019; Miranda-Agripino and Rey, 2020 a,b). We also do not evaluate the interaction between real-economy and financial variables, because we estimate the effects of financial conditions of the US on stocks and credit of other countries, which are also financial variables. However, our main theoretical motivation does come from the theoretically and empirically grounded consensus in the literature, reached after the Great Recession, revised for instance by Isohätälä et al. (2016), Brunnermeier and Sannikov (2016) and Gertler and Gilchrist (2018). This literature emphasizes the role of borrowers' balance sheets in constraining access to credit when capital markets are imperfect or the nonlinear amplification mechanisms that characterize financial crises. The strength of a bank's balance sheet affects access to credit and thus the possibility to spend on the side of firms and households. In turn, financial collapses are characterized by borrower's balance sheets severely contracted, which lead to significant disruptions of credit flows. In this way, important declines in spending and

[3] See Nakamura and Steinsson (2018) for a recent summary on the non-neutrality of monetary policy.

economic activity are expected to follow. All these mechanisms place the role of funding as a priority to understand crises and carry out stabilization policies.

Regarding the second identification issue, note that moving from the domestic economy to international grounds opens the door to another problem related to the identification of international shocks. Namely, US shocks might be correlated with global financial and economic activity shocks which cannot be ruled out only by stressing out the dominance of the US economy. This point has been explored for instance by Chudik and Pesaran (2015) and Cesa-Bianchi et al. (2020). Lacking to control for these common factors likely render omitted-variables bias to the estimated effects on a domestic-economy level. This point has been mainly overlooked by the extant literature on (international) vulnerable growth, and the literature on the transmissions of (international) credit imbalances, which have mainly focused on a few number of countries or even on individual countries using granular micro-data.

Our study is also related to the large corpus of theoretical and empirical literature that has expanded the credit-channel to international grounds, and therefore, has contributed to the explanation of the transmission of financial shocks across the world economy (Peek and Rosengren, 1997; Cetorelli and Goldberg, 2011; Ivashina et al., 2015; Bruno and Shin, 2015; Choi, 2018; Choi et al., 2018; Baskaya et al., 2017; Gete and Melkadse, 2018; Braüning and Ivashina, 2020a; Di Giovanni et al., 2029; among others). We revise this literature and connect it with our contributions in the next section, which in short aim to help regulators to foresee future risks to funding opportunities for domestic investment and consumption, and therefore to economic activity, after a financial shock to the US economy has been observed (as occurred for instance during the Great Recession). We also seek to document the main way in which vulnerable growth occurs, which is precisely through the propagation of financial shocks across the global financial markets, i.e., via vulnerable funding.

The rest of this document is organized as follows: Section two briefly revises two perspectives in the literature that can explain the transmission of financial conditions of the US to the international funding markets, namely the credit view and the portfolio view and also revise the two main explanations underlying vulnerable funding, market depth and market connectedness. The third section consists of our methodology. Section four describes our data and sources, and presents details about the construction of our macroeconomic and financial global factors. Section five contains our main empirical results and discussion. Section six concludes.

2. International spread of US financial conditions

In addition to the vulnerable growth literature summarized in the introduction, our study is related to two different sets of studies: Those who emphasize the channels through which financial shocks transit from a central economy (generally the US) to the rest of the global markets, and those who examine the macroeconomic determinants of financial vulnerability to external shocks. Both literatures are too rich as to be summarized in this subsection, so we only focus on those studies that directly provide a baseline for understanding our main results. In the former group of studies we find a subset of articles that highlight the role of credit in the international propagation of financial shocks, which we label as the *credit view*, and a second subset that emphasizes the transmission of financial shocks trough expectations, which we include in the *portfolio view* of the transmission of shocks.

In the second group of studies we find a great majority of articles that have pointed-out to size and depth of the financial markets as the main determinants of financial vulnerability to external shocks, hence they are labeled as the *financial development determinant*, and a second subset that instead has stressed out the importance of financial connectedness across the global financial markets as the main explanatory factor, labeled the *financial connectedness determinant*. Both channels and determinants are important for our different definitions of financial conditions, based on first and second moment indicators. The classification does not pretend to be either exhaustive or exclusive. Indeed, in the referenced studies the channels and determinants are closely interviewed. For instance, as highlighted by Alfaro et al. (2007) the role of local financial markets is crucial in enabling foreign direct investment. The more developed the local financial markets, the easier it is for credit-constrained entrepreneurs to start their own business. Large varieties of intermediate goods imply positive spillovers to the final goods sector and, as a consequence, financial markets allow the backward linkages between foreign and domestic firms to turn into FDI spillovers.

Hence, our revision is more oriented to serve as a starting point to understand the empirical results in the next section, and how they relate to our working hypothesis explained in the introduction about the existence of vulnerable funding episodes following first and second moment shocks to financial conditions in the US.

2.1. The channels

A. The international credit view

According to this literature external factors, such as the US interest rates and global financial conditions, are key determinants of capital flows, especially in the short run. Which is important because as highlighted by Kalemli-Özcan et al. (2020), there is evidence about a strong association between capital flows, GDP volatility, and financial crises. This general view consists of understanding that international creditors may react to a change of financial conditions, including monetary policy stances in their original economies, by reducing their exposition to foreign markets, to satisfy risk-taking constraints on their international credit portfolio holdings. Thus, as emphasized by Braüning and Ivashina (2020a), some intended consequences of the US monetary within its domestic economy, may end up having intended consequences on a global basis (i.e. spillover of "prudent risk-taking" or "productive risk-taking").

In these lines, Bruno and Shin (2015) highlight the role of financing costs of banks, which are closely tied to the reference policy rate chosen by the central bank. If funding costs affect decisions on how much exposure to take on, monetary policy will then affect the economy through greater risk-taking by the banking sector. Di Giovanni et al (2019) also document that an easing in global financial conditions leads to lower borrowing costs and to an increase in local lending. The shocks on credit can potentially transit via international banks as in Cetorelli and Goldberg (2011), foreign banks lending elsewhere as in Braüning and Ivashina (2020b) and Ivashina et al. (2015), via domestic banks borrowing from foreign banks and global investors over the global financial cycle as in Baskaya et al (2017) or even via credit trade by multinational establishments (Lin and Yee, 2018).

B. The international portfolio view

Even if we abstract from the direct link that provides lending, it could also be the case that if a peak of uncertainty in the US, associated to a worsening of financial conditions, is interpreted as signal of future higher domestic vulnerability in other countries, such an increase may lead to higher precautionary savings which do not remain within the domestic economies but that instead flow abroad, reducing domestic demand (Fernández-Villaverde et al., 2011) and similarly to a contraction of banks' credit supply after facing greater uncertainty, which can be rationalized by the arguments explored by Bordo et al. (2016), Valencia (2016), Caldara et al. (2016), Alessandri and Mumtaz (2019) and Alessandri and Botero (2020).

We contribute to the previous literature on the transmission channels in two ways: first, we focus on the most vulnerable market scenarios, automatically identified by estimating Credit at Risk and Equity at Risk statistics, which has not been done before (all the aforementioned literature focus on the average scenarios, and most of them on a few number or individual countries). In this way, we acknowledge the non-linear dimension emphasized by the consensus of the macroeconomic literature in recent years, necessary to explain economic collapses (Isohätälä et al., 2016; Brunnermeier and Sannikov, 2016; Gertler and Gilchrist, 2018). Second, we jointly analyze the impacts of first moment shocks proxied by the NFCI, and second moment financial conditions proxied by the index of financial uncertainty of Ludvigson et al. (2021). Thus we are able to disentangle the whole effects of financial conditions on the global economy. All in all, our results emphasize the role of the portfolio view for the propagation of second moment financial condition shocks and of the credit view to understand the propagation of first moment financial conditions shocks.

2.1. The Determinants

A. Size and depth of the domestic financial market

The previous literature has reported an asymmetric impact of global financial conditions on economic activity of emerging and advanced economies. For example, Carrièrre-Swallow and Céspedes (2013) find that in comparison to the U.S. and other developed countries, emerging economies suffer much more severe falls in investment and private consumption following an exogenous uncertainty shock. They present evidence on the correlation of the dynamics of investment and consumption with the depth of financial markets. The authors emphasize the role of financial institutions and argue that the lack of development of local financial markets can limit the economy's ability to take advantage of potential FDI spillovers. Alfaro et al (2004) evaluate the various links among FDI, financial markets, and economic growth. They conclude that FDI alone plays an unclear role for economic growth. Instead it is well-developed financial markets and institutions that enable a country to take advantage from increases in foreign investment. Kalemli-Özcan (2019) shows that changes in US monetary policy affect capital flows in and out of emerging markets more than they do in advanced economies, since the capital flows of emerging markets are more risk sensitive, and US policy affects the risk sentiments of global investors.

Other authors such as Braüning and Ivashina (2020a) document that global bank flows driven by U.S. monetary policy affect credit conditions in emerging markets, at the firm level, which confirms that the contraction of credit by global banks is not compensated by an increase in credit by local banks. On the contrary it leads to a general credit contraction, an increasing in interest rate spreads, and finally to a lower probability of refinancing.

The same narrative can be tracked in the previous literature regarding the transmission of international stock market shocks to domestic economies across the world. For instance, Bhattarai et al (2020) document that unanticipated changes in US uncertainty have significant effects on financial and macroeconomic emerging market economies. The transmission is traced back to a depreciation of the local currency of domestic economies, which leads to a decline in local stock markets, increases long-term interest rate spreads in relation to the US, and is followed by a decrease in capital inflows into the domestic economies.

B. *Financial connectedness with the US*

It is important to think of this literature as a complement of the studies in literal A, which emphasizes the role of size and depth of the domestic markets that receive the shock, instead of as an alternative explanation. To illustrate this point, Fink and Schüler (2015) emphasize the importance of financial linkages with the US rather than via bilateral trade to explain the propagation of financial condition shocks across the global economy. However, precisely for this reason the transmission to emerging market economies (EME) may occur to a different extent than the transmission to advanced economies. Fink and Schüler (2015) find that, indeed, an adverse shock to the overall US financial system dries up capital flows from the US to the EME and that this decline in cross-border lending results in tighter financing conditions for the EME.

Alfaro and Chen (2012), using granular data investigate the way in which multinationals around the world responded to the 2008 crisis relative to local firms. They explore three channels through which FDI affects establishment performance: production linkages, financial linkages, and multinational networks. These authors' results point-out to an important although heterogeneous role of FDI flows at explaining multinational firms' performance during the

Global Financial Crisis. They emphasized both the role of FDI linkages in the international transmission of shocks and the important interaction of the various facets that determine such transmissions, from financial constraints considerations to the engagement of some firms with vertical production linkages.

Lin and Ye (2018) explore a trade credit channel through which FDI firms can propagate global liquidity shocks to host countries, despite these host countries implementing tight controls on portfolio flows. This is important because in practice, while many developing countries impose tight restrictions on non-FDI flows, they are significantly open to FDI inflows. These authors show that indeed a positive global liquidity shock eases raising international funds for FDI firms. This in turn, strengthens FDI firms' advantage in trade credit provision to local downstream firms. In short, there exists a trade credit channel through which FDI firms can propagate global liquidity shocks to host economies despite the presence of tight controls on non-FDI financial flows.

In terms of contributions, our multi-country and comprehensive approach, allows us to test what factor explains better the heterogeneous dynamic of Credit at Risk and Equity at Risk indicators that we estimate for the cross-section of countries. We find that vulnerability of credit markets is better explained by the size or depth of credit markets while financial connectedness to the US, measured as the relative importance of US foreign direct investment to a country's GDP, better explains vulnerability of stock markets.

3. Methodology

To avoid the criticisms mentioned in the introduction regarding the likely endogeneity of financial first and second moment shocks with respect to credit and stock markets within a single economy, we estimate multi-country factor augmented quantile-regression models. Our models directly consider the influence of common real and financial factors of a global nature, on the domestic economic series. Thus, they allow us to better isolate the causal effects of financial conditions on funding markets around the world.

Our base-line specification for each country *i* is given by Equation 1:

$$y_{i,t+h}(\tau) = \alpha_{0i}(\tau) + \beta_{0i}(\tau)y_{i,t} + \beta_{1i}(\tau)us.fc_t + \delta_i(\tau)'X_t, \quad (1)$$

where, $\mathrm{i} = 1, \ldots \mathrm{N}$, refers to the country, $\mathrm{h} = \{0,1,4\}$, to the forecasting- horizon, and $\tau = \{0.05,0.10.0.20,0.50\}$ to the quantile of the dependent variable. $y_{i,t+h}$ is either the quarterly change of real credit growth in logarithms (Credit at Risk) or the quarterly change of the stock price index in logarithms (Equity at Risk), at time horizon $t + h$. On its side, $us.fc_t$ is the US financial condition indicator, which can be either the *NFCI* of the Chicago's Fed or the Financial Uncertainty Index provided by Ludvigson et al. (2021), publicly available on the we page of the authors. X consists of a global macroeconomic factor and a global financial factor. $\alpha_0(\tau), \beta_0(\tau), \beta_1(\tau)$ and $\delta(\tau)$ denote the parameters corresponding to the τ-th quantile.

We emphasize that $y_{i,t+h}(\tau)$ is a conditional quantile of the response variable, and for this reason there is not a random term in equation 1. In other words, $y_{i,t+h}(\tau)$ characterizes $y_{i,t+h}$ but it is deterministic in nature. Nevertheless, we can present Equation 1 alternatively in the following way:

$$y_{i,t+h} = \alpha_{0i}(\tau) + \beta_{0i}(\tau)y_{i,t} + \beta_{1i}(\tau)us.fc_t + \delta_i(\tau)'X_t + \varepsilon_{i,t}(\tau)\ , \tag{2}$$

where $\varepsilon_t(\tau)$ is a random noise that is assumed to follow the following quantile-restriction $P\left[\varepsilon_{i,t}(\tau) \leq 0 \middle| \alpha_{0i}(\tau) + \beta_{0i}(\tau)y_{i,t} + \beta_{1i}(\tau)us.fc_t + \delta_i(\tau)'X_t\right] = \tau$. The presentation of the model in equation 2 emphasizes the factor structure of the CaR and EaR statistics. The model for each country is estimated using individual conditional quantile regressions as proposed by Koenker and Basett (1978), but $y_{i,t+h}$ in all countries are a function of common factors, $us.fc_t$ and X_t, which do not have cross-sectional variation but only vary through time, via a country-specific intercept (α_{0i}) and country-specific slope coefficients (β_{0i}, β_{1i}, δ_i). All the variables were normalized before estimation to have zero mean and unitary variance. In this way, we are able to compare the magnitude of the effects across different countries.

The model in Equation 1 expands a traditional conditional mean regression, in the sense that it explains the whole conditional time-series distribution of credit growth and stock returns. In particular, $y_{i,t+h}(\tau)$ solves the following optimization problem:

$$y_{i,t+h}(\tau) = \mathrm{argmin}_{\beta(\tau)} E\left[\rho_\tau\left(y_{i,t+h}(\tau) - \hat{y}_{i,t+h}(\tau)\right)\right], \tag{3}$$

where $(\tau) = [\alpha_0(\tau), \beta_0(\tau), \beta_1(\tau), \delta(\tau)]$, $\hat{y}_{i,t+h}(\tau) = \alpha_{0i}(\tau) + \beta_{0i}(\tau) y_{i,t} + \beta_{1i}(\tau) us.fc_t + \delta_i(\tau)' X_t$, and $\rho_\tau(\cdot)$ is a loss function, given by $\rho_\tau(\varepsilon) = (1-\tau) I_{\{\varepsilon<0\}} |\varepsilon| + \tau I_{\{\varepsilon>0\}} |\varepsilon|$, with $I_{\{\varepsilon<0\}}$ taking the value of 1 when the subscript is true and 0 otherwise. As it is well known, the mathematical formulation in Equation 3 leads to the solution of a linear programming optimization problem that we have omitted here. Its basic structure and the counterpart algorithm solution can be found in Koenker (2005).

Quantile regressions have been employed in the factor models literature, since at least Ando and Tsay (2011). We estimate the global factors using PCA, following the tradition of the factor literature, as described for example by Bai and Ng (2008, 2020) and Stock and Watson (2010), and also the approach of aforementioned studies on GaR. An alternative to Equation 1 would be incorporating the global factors as done by Chudik and Pesaran (2015) using the cross-sectional means for the variables in the data set, and this would result in a quantile factor model in the form of Harding et al. (2020). Both, these authors' approach and our approach are inspired by the necessity to incorporate common factors to model the dynamics of the cross-sectional units, which are fundamental when conducting multinational comparisons, in order to reduce the risk of omitting relevant confounding variations.

Note as well that we do not have a balanced-panel (and we do not require it), our approach is more flexible than that, in the sense that our factors use all the available cross-sectional units at each period in the sample, but the country-specific estimates depend on the number of time-series units available for each country, which in most cases run from 1960:1Q to 2019:4Q, and only in two cases consist of shorter samples (which are indicated in the results).

4. Data

Our dataset includes a set of macroeconomic and financial variables for advanced and emerging economies and US data on financial conditions. Specifically, we use a long quarterly data panel constructed and provided by Monnet and Puy (2019), which covers real Gross Domestic Product (GDP), credit, consumer prices, nominal stock prices, and sovereign bond yields for advanced and emerging countries over the whole post-war period. Compared to other 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 is around 20% to 30% for advanced economies, and more 100% for emerging economies. More specifically, real GDP is available for 37 countries, real credit for 45 countries, consumer prices for 48, nominal stock prices for 25 countries and bond yields for 18, with a sample size that ranges between 1950-Q1 and 2019-Q4 per country[4]. We restrict our sample to start in 1960-1Q because of poor data quality for the earlier periods (we observed very extreme values and large volatility). For the purposes of our analysis, we transform our variables in order to achieve stationarity before estimation. Table A2 in the Appendix shows the transformations applied to each series and Figure A1 plots both the untransformed and transformed series with their associated unit root tests[5].

As for US data on financial conditions, we use either the National Financial Condition Index[6] or the financial uncertainty indicator proposed by Ludvigson et al. (2021)[7]. On the one hand, following the seminal work of Adrian et al. (2019), NFCI is considered to be one of the most relevant predictors of the lower conditional quantiles of output growth for the US (e.g., Arrigoni et al., 2020; Brownlees and Souza, 2020; Beutel et al., 2020; Deuskar et al., 2020). Based on Brave and Butters (2012), the NFCI is a weighted average of 105 measures of financial activity, each one scaled to have zero mean and one standard deviation. Positive NFCI values imply that US financial conditions are tighter than average. Since the NFCI has weekly periodicity, for our analysis we aggregated it by taking the quarter averages for the overall sample, starting at 1971-Q1. This implies that for our econometric estimations that include this variable, the sample is reduced to around 200 observations. On the other hand, the financial uncertainty index is constructed by Ludvigson et al. (2021) using a rich-dataset of variables that fully characterize US financial markets. The authors of the index estimate a factor model for the large-dataset, and predict each variable using their latent factor structure. Then, they estimate the time-varying conditional volatility of each series residuals and average across all of them, in order to get the financial uncertainty indicator.

As stated above, in our estimations we include a global macroeconomic factor and a global financial factor to control for the commonality of business and financial cycles previously

4 See Table A1 in the Appendix for details on data availability, Table A2 for details on transformations of the variables, and Table A3 for details on summary statistics.

5 We test for unit roots using the Augmented Dickey-Fuller (ADF).

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

7 The Financial Uncertainty indicator is available for the US in the web page of one of its authors, at: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes

emphasized by the literature. The central idea of our approach is to summarize fluctuations in macroeconomic and financial variables for a large and heterogeneous panel of advanced and emerging economies by using factor models. In particular, we estimate two global factors: the first factor, which we refer to as the global financial factor (N=89; T=240, from 1960Q1 to 2019Q4) contains real credit growth, stock returns and changes in sovereign bond yields; and the second factor, which we refer to as the global macroeconomic factor (N=174; T=240, from 1960Q1 to 2019Q4), includes real GDP growth, inflation, on top of the above-mentioned variables.

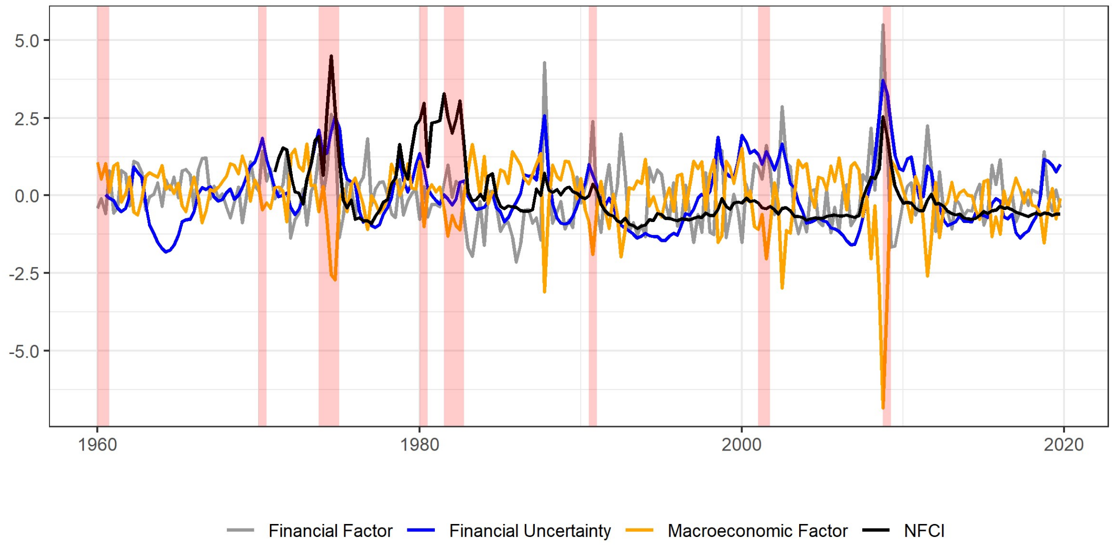
We estimate these common factors by a two-step procedure that combines first-step estimation via Principal Component Analysis (PCA)[8] with the Kalman filter, where the latter is used to compute recursively the expected value of the common factors, which is iterated until convergence of the Expected-Maximization (EM) algorithm (Doz *et al.*, 2012). This procedure is especially relevant for our work as we deal with some missing data for specific countries at the end of the sample. We compute the factors from the stationary variables and assume that can be represented by a VAR(1) process. However, the two factors (global macroeconomic and financial) estimated using the two –steps algorithm are very similar to the ones computed by direct estimation via PCA, thus we opt for reporting only the latter in our results (see Table A3).

Figure 1 plots the NFCI jointly with the global macroeconomic and financial factors over the sample period. Consistent with Miranda-Aggrapino and Rey (2020), we find that our global factors point-out to the existence of a global cycle that commoves with the U.S. recession periods as identified by the NBER (red shaded areas). These global factors, the NFCI and the financial uncertainty index share a pronounced contemporaneous common component, especially around the global financial crisis. In this period, we notice a sharp movement of the global factors and a tightening in US financial conditions. This fact suggests that, in order to explore the international transmission of financial fragility in the US to the conditional distribution of global credit markets and stock markets, we should control for the contemporaneous global and financial cycles. Thus, we should focus on the additional "marginal" information provided by the indicator of financial fragility in the US. Additionally,

[8] In order to estimate principal components in the first stage, missing values are imputed by the respective country-specific variable's average.

we observe that the NFCI and the financial uncertainty index share some common spikes, e.g. around the 1973-1975 recession due to the oil crisis coupled with the stock market crash, or during the global financial crisis, but appear to be capturing different aspects of US financial fragility. In particular, the NFCI is more volatile and moved up notably during the recession periods in the early 80s, while the uncertainty index stayed subdued over the same period. However, the opposite happened in the late 1990s and during the collapse of the speculative dot-com bubble in the early 2000s. Moreover, during 2018-2019 the uncertainty index rose significantly while the NFCI remained stable.

Figure 1.Global factors and US financial conditions



Sources: Chicago National Financial Condition Index (NFCI) and author's computation.
Note: Standardized variables. Time span 1971Q1 to 2019Q4. Red shaded area represents NBER recessions at the end of the period.

Finally, to assess cross-country heterogeneity, we construct three variables related to the size of credit and stock markets, respectively, and financial interconnection with the US. Specifically, we measure the size of credit markets by the annual average of the credit to GDP ratio for each country and the size of stock markets by the annual average of the market capitalization to GDP ratio. This data has been collected from the World Bank database[9] and, in both cases, the time spam goes from 1960 to 2019. Financial interconnection with the US is measured by the total direct investment of the US as a percentage of the country's GDP (for the sample period 1989 to 2019). To this end, we compute for each country the maximum value of US

[9] 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.

investment inflows relative to its GDP[10]. We use historical data on US direct investment abroad from the National Bureau of Economic Research and nominal GDP from the International Monetary Fund statistics.[11]

5. Results

First, we present our estimation results of the impact of US financial conditions shocks on credit growth and stock returns. We distinguish between changes in the first moment of financial conditions (as measured by the NFCI) and changes in the second moment of financial conditions (as measured by the index of financial uncertainty proposed by Ludvigson et al. (2021)). Then, we assess the heterogeneity on the vulnerability of credit and stock markets to US financial conditions across countries. To this end, first, we graphically show our results sorting the countries according to different measures related with the size of credit and stock markets, and the relative importance of US foreign investment for each country. Finally, we carry out cross-sectional regressions that use as input the quantile slopes of CaR and EaR estimated in the first round of regressions, and as explanatory variables the ones mentioned above.

5.1. Impact of NFCI shocks on global markets

Table 1 summarizes the estimation results for real credit growth as the dependent variable for quantiles $\tau = \{0.05,0.10.0.20,0.50\}$ and for forecasting- horizons $h = \{0,1,4\}$. We run two different regressions. The first one only includes the NFCI while the second one controls for the global financial and macroeconomic factors. The table reports the following information: the first and last quartiles of the distribution of estimated coefficients (q25-q75), the proportion of countries for which the variable is statistically significant at 90% confidence level (Sig.) and, for the NFCI, additionally it is showed the proportion of countries that displays negative or significant quantile slopes coefficients (Sig.<0).

[10] Results are robust when we use the average instead of the maximum value.
[11] See Table A5 in the Appendix for information on these variables.

Table 1: Quantile regressions, Impact of NFCI on real credit growth (CaR)

		$\tau =$			
		0.05	**0.1**	**0.2**	**0.5**
Regressions for $h = 0$					
		US financial conditions indicator			
$NFCI_t$	q25-q75	[-0.32;0.07]	[-0.22;0.02]	[-0.14;0.05]	[-0.05;0.08]
	Sig.<0	0.25	0.16	0.14	0.07
		US financial conditions indicator + Global factors			
$NFCI_t$	q25-q75	[-0.25;0.02]	[-0.24;0.01]	[-0.16;0.02]	[-0.06;0.07]
	Sig.<0	0.18	0.14	0.25	0.07
$G\_Financial_t$	q25-q75	[0.02;0.56]	[0.00;0.56]	[0.03;0.52]	[0.13;0.52]
	Sig.	0.25	0.34	0.45	0.5
$G\_Macroeconomic_t$	q25-q75	[-0.08;0.63]	[-0.1;0.52]	[-0.05;0.53]	[0.11;0.54]
	Sig.	0.27	0.3	0.45	0.5
Regressions for $h = 1$					
		US financial conditions indicator			
y_{it}	q25-q75	[0.05;0.32]	[0.07;0.36]	[0.06;0.35]	[0.09;0.43]
	Sig.	0.30	0.48	0.59	0.70
$NFCI_t$	q25-q75	[-0.28;-0.02]	[-0.24;-0.06]	[-0.19;-0.01]	[-0.08;0.02]
	Sig.<0	0.23	0.25	0.30	0.07
		US financial conditions indicator + Global factors			
y_{it}	q25-q75	[0.06;0.30]	[0.05;0.35]	[0.09;0.37]	[0.09;0.43]
	Sig.	0.36	0.48	0.57	0.68
$NFCI_t$	q25-q75	[-0.26;-0.02]	[-0.24;-0.03]	[-0.17;-0.05]	[-0.06;0.06]
	Sig.<0	0.16	0.27	0.25	0.02
$G\_Financial_t$	q25-q75	[-0.45;0.37]	[-0.27;0.23]	[-0.16;0.17]	[-0.08;0.19]
	Sig.	0.30	0.23	0.25	0.30
$G\_Macroeconomic_t$	q25-q75	[-0.4;0.40]	[-0.24;0.23]	[-0.11;0.26]	[0.00;0.27]
	Sig.	0.30	0.23	0.27	0.39
Regressions for $h = 4$					
		US financial conditions indicator			
y_{it}	q25-q75	[0.24;0.57]	[0.32;0.55]	[0.34;0.56]	[0.33;0.62]
	Sig.	0.61	0.80	0.89	0.98
$NFCI_t$	q25-q75	[-0.41;0.02]	[-0.28;-0.02]	[-0.22;0.00]	[-0.09;0.02]
	Sig.<0	0.25	0.20	0.34	0.18
		US financial conditions indicator + Global factors			
y_{it}	q25-q75	[0.29;0.56]	[0.27;0.60]	[0.33;0.58]	[0.34;0.60]
	Sig.	0.68	0.77	0.84	0.98
$NFCI_t$	q25-q75	[-0.32;-0.01]	[-0.31;-0.02]	[-0.22;-0.02]	[-0.07;0.04]
	Sig.<0	0.27	0.30	0.3	0.14
$G\_Financial_t$	q25-q75	[-0.48;0.11]	[-0.32;0.19]	[-0.18;0.20]	[-0.05;0.15]
	Sig.	0.16	0.09	0.20	0.16
$G\_Macroeconomic_t$	q25-q75	[-0.49;0.05]	[-0.37;0.15]	[-0.23;0.16]	[-0.03;0.16]
	Sig.	0.16	0.20	0.20	0.18

Note: Sig. denotes proportion of countries for which the variable is statistically significant at 90% confidence level; q25-q75 shows the first and third quartiles of the estimated coefficients. Intercepts are omitted in the table. Standard errors are based on bootstrap with 1000 replications. Sample: 1971Q1 to 2019Q4 for 44 countries, except for Bolivia (to 2019Q3), Iceland (to 2018Q4) and Taiwan (to 2018Q4).

Three main messages emerge from the results in Table 1. First, the impact of the NFCI on real credit growth is more frequently (and significantly) negative on the lower quantiles than on the central quantiles of credit growth. In other words, the proportion of countries for which the effect is significant, is much higher in the lower quantiles. This result suggests that US financial fragility is an important predictor of downside risks to real credit growth in the global economy. Second, our results hold when we control for global financial and macroeconomic factors, i.e., the performance of the model including the global factors is basically indistinguishable from the model including only the NFCI. Third, the results also hold irrespective of the forecasting- horizon (h=0,1,4) but the highest percentage of countries for which the impact of NFCI on the quantile at $\tau = 0.05$ (0.10) of real credit growth is statistically significant and negative is obtained when h=4, with 27% (30%) for 44 countries. This latter fact suggests that the global economy requires one year to fully transmit most of the first moment shocks of US financial conditions to the rest of the credit markets in the world, which is consistent with a credit view explanation of the transmission of shocks, i.e., deterioration of financial conditions seem to generate a reduction of international funding sources for financing domestic investment which fully materializes one year after the shock.

Interestingly, forecasting power of NFCI on the conditional distribution of credit is more heterogeneous than the effect of the other covariates in all our specifications. That is, financial conditions of the US clearly impact the negative tail of credit growth of a higher number of countries than in the case of the average quantiles, while the other variables, whether they are global common factors or idiosyncratic characteristics, exert a more homogeneous effect across the conditional distribution of credit.

From Table 1 we also notice that the impact of financial conditions in the United States is very heterogeneous across countries. While it is a relevant predictor of negative credit dynamics at least four quarters ahead for around 25-30% of our sample, it is not for the rest of the countries. Moreover, the impact of the three global factors, namely, two global factors and the financial conditions index of the US, present a large variability across countries. That is, in most of the cases the effects contained between the first and the third quartiles of the cross-sectional distribution of countries include both positive and negative magnitudes, meaning that global factors impact heterogeneously credit creation around the world.

Table 2 summarizes the estimation results for stock returns as the dependent variable. Again, for each quantile of the dependent variable ($\tau = \{0.05, 0.10.0.20, 0.50\}$) and forecasting-horizon ($h = \{0,1,4\}$), we run two models. The first model only includes the NFCI while the second also considers controls for the global financial and macroeconomic factors. The table reports the following information: the first and last quartile of the distribution of estimated coefficients (q25-q75), the proportion of countries for which the variable is statistically significant at 90% confidence level (Sig.); for the NFCI, additionally it is shown the proportion of countries that is associated with negative and significant coefficients (Sig.<0).

Results show that the highest impact of US financial conditions at the left tail of conditional stock returns are observed when h=0, i.e., NFCI significantly explains downside risk in stock markets in a contemporaneous fashion. This key result is observed even if we control for global financial and macroeconomic factors, as the percentage of countries for which the NFCI coefficient is statistically significant goes from 32% (τ =0.05 quantile) to 48% (τ =0.10 quantile), out of 25 countries. Interestingly, the contemporaneous impact at the median is significant for a larger proportion of countries (60%) but this percentage drops to 12% when we control for the global factors. At horizons h=1 and h=4, the effects of NFCI on stock markets are less pronounced, both at the lower tail and at the central quantiles.

An interesting pattern can be noticed as well in Table 2 that confirms the US as the likely origination of shocks to the global economy, which agrees with previous literature on global cycles, and which also validates our multinational approach. Namely, at h=1, local financial conditions in the United States, exert a significant impact in around 4-12% of the countries of our sample, for quantiles between τ= 0.05 to 0.20, while the global financial factors impact the same quantiles for 12-16% of the countries and the global macroeconomic factors for 0-12%. In contrast, when h=4, the impact of the domestic financial conditions of the US only exert a significant influence in 4-12% of the countries, while the global financial and macroeconomic factors have gained in significance as to affect 40-52% and 28-64% of countries, respectively. This would be the case if one year after the US shock, this original shock has been fully transmitted to the global economy, and the non-linear amplification mechanisms operating in financial markets on a global scale are responsible for the newest sources of financial fragility to the global economy.

Table 2: Quantile regressions, Impact of NFCI on stock markets (EaR)

		$\tau =$			
		0.05	**0.1**	**0.2**	**0.5**
Regressions for $h = 0$					
		US financial conditions indicator			
$NFCI_t$	q25-q75	[-0.65;-0.24]	[-0.47;-0.2]	[-0.37;-0.08]	[-0.24;-0.08]
	Sig.<0	0.36	0.56	0.68	0.60
		US financial conditions indicator + Global factors			
$NFCI_t$	q25-q75	[-0.34;0.00]	[-0.24;0.02]	[-0.15;-0.01]	[-0.05;0.04]
	Sig.<0	0.32	0.48	0.36	0.12
$G\_Financial_t$	q25-q75	[-0.79;-0.41]	[-0.85;-0.42]	[-0.83;-0.39]	[-0.78;-0.35]
	Sig.	0.60	0.68	0.76	0.88
$G\_Macroeconomic_t$	q25-q75	[-0.09;0.25]	[-0.1;0.26]	[-0.14;0.23]	[-0.06;0.21]
	Sig.	0.20	0.08	0.40	0.24
Regressions for $h = 1$					
		US financial conditions indicator			
y_{it}	q25-q75	[0.18;0.51]	[0.19;0.47]	[0.18;0.41]	[0.26;0.37]
	Sig.	0.56	0.64	0.80	0.92
$NFCI_t$	q25-q75	[-0.23;0.01]	[-0.2;0.00]	[-0.18;-0.02]	[-0.1;0.01]
	Sig.<0	0.12	0.16	0.16	0.16
		US financial conditions indicator + Global factors			
y_{it}	q25-q75	[-0.01;0.29]	[0.08;0.33]	[0.15;0.37]	[0.16;0.38]
	Sig.	0.08	0.32	0.48	0.56
$NFCI_t$	q25-q75	[-0.21;0.05]	[-0.18;0.01]	[-0.15;0.00]	[-0.07;0.01]
	Sig.<0	0.12	0.04	0.08	0.16
$G\_Financial_t$	q25-q75	[-0.35;0.09]	[-0.53;-0.07]	[-0.41;-0.09]	[-0.24;-0.01]
	Sig.	0.12	0.12	0.16	0.00
$G\_Macroeconomic_t$	q25-q75	[-0.20;0.40]	[-0.31;0.03]	[-0.26;-0.09]	[-0.18;-0.03]
	Sig.	0.08	0.00	0.12	0.00
Regressions for $h = 4$					
		US financial conditions indicator			
y_{it}	q25-q75	[-0.10;0.29]	[0.00;0.17]	[-0.02;0.10]	[-0.09;0.03]
	Sig.	0.20	0.16	0.08	0.08
$NFCI_t$	q25-q75	[-0.28;0.14]	[-0.14;0.09]	[-0.09;0.06]	[-0.06;0.04]
	Sig.<0	0.04	0.04	0.04	0.12
		US financial conditions indicator + Global factors			
y_{it}	q25-q75	[-0.07;0.16]	[-0.13;0.17]	[-0.11;0.12]	[-0.10;0.04]
	Sig.	0.00	0.04	0.08	0.08
$NFCI_t$	q25-q75	[-0.18;0.21]	[-0.17;0.13]	[-0.08;0.09]	[-0.07;0.06]
	Sig.<0	0.04	0.12	0.04	0.08
$Financial_t$	q25-q75	[-0.96;-0.33]	[-0.79;-0.46]	[-0.64;-0.34]	[-0.36;-0.08]
	Sig.	0.40	0.52	0.52	0.36
$G\_Macroeconomic_t$	q25-q75	[-0.82;-0.36]	[-0.88;-0.36]	[-0.62;-0.40]	[-0.38;-0.11]
	Sig.	0.28	0.56	0.64	0.52

Note: Sig. denotes proportion of countries for which the variable is statistically significant at 90% confidence level; q25-q75 shows the first and last quartile of the estimated coefficients. Standard errors are based on bootstrap with 1000 replications.

Once again, the effects across countries at the lowest quantiles of the stock market growth are heterogeneous. That is, the interquartile range of the cross-sectional distribution of countries includes both positive and negative values, not only for the financial condition index, but also in the case of macroeconomic and financial global factors, pointing out to a heterogeneous risk-sharing picture across countries. While an important fraction of the countries react negatively to a deterioration of either the financial conditions in the US or the two global factors, most of them do not react or even react positively to the shock.

One way in which the transmission of shocks may occur across countries is through spillovers effects of the "prudent risk-taking" or "productive risk-taking" channel of monetary policy. This is a channel that leads to increased risk-taking by banks in response to monetary policy easing, which is consistent with traditional portfolio allocation models. Namely, lower policy rates make riskier investments more attractive.

Importantly, the largest effects of US financial fragility on credit markets are observed one year after the realization of the shock, suggesting that US financial conditions can be used as a predictor of the future vulnerability of domestic credit conditions by regulators and central banks around the globe. On the contrary, the effects on stock markets are mainly contemporaneous, which prevents the use of this indicator to forecast future prices or as an early warning indicator that alerts on future limitation of internal (equity) funding.

5.2. *Impact of US financial uncertainty shocks on global markets*

5.2.1. *Global credit markets*

Similar to Table 1, Table 3 summarizes the estimation results for credit growth as the dependent variable but this time bringing to play the US financial uncertainty index instead of the NFCI.

Table 3: Quantile regressions, Impact of Financial Uncertainty on real credit growth

		$\tau =$			
		0.05	**0.1**	**0.2**	**0.5**
Regressions for $h = 0$					
		US financial uncertainty indicator			
$F\_Uncertainty_t$	q25-q75	[-0.23;0.05]	[-0.2;0.02]	[-0.13;0.02]	[-0.07;0.02]
	Sig.<0	0.14	0.20	0.25	0.23
		US financial uncertainty indicator + Global factors			
$F\_Uncertainty_t$	q25-q75	[-0.29;0.02]	[-0.21;-0.02]	[-0.15;0.00]	[-0.1;0.05]
	Sig.<0	0.16	0.25	0.25	0.20
$G\_Financial_t$	q25-q75	[-0.15;0.57]	[0.07;0.54]	[0.05;0.61]	[0.17;0.64]
	Sig.	0.36	0.48	0.57	0.68
$G\_Macroeconomic_t$	q25-q75	[-0.13;0.48]	[-0.09;0.52]	[0.00;0.62]	[0.10;0.67]
	Sig.	0.32	0.50	0.55	0.64
Regressions for $h = 1$					
		US financial uncertainty indicator			
y_{it}	q25-q75	[0.00;0.25]	[-0.03;0.28]	[0.09;0.30]	[0.13;0.41]
	Sig.	0.30	0.39	0.64	0.73
$F\_Uncertainty_t$	q25-q75	[-0.22;0.04]	[-0.17;0.01]	[-0.1;0.00]	[-0.09;-0.02]
	Sig.<0	0.18	0.20	0.23	0.25
		US financial uncertainty indicator + Global factors			
y_{it}	q25-q75	[-0.09;0.25]	[-0.01;0.26]	[0.05;0.27]	[0.09;0.36]
	Sig.	0.30	0.43	0.57	0.73
$F\_Uncertainty_t$	q25-q75	[-0.22;0.06]	[-0.14;0.04]	[-0.12;0.00]	[-0.07;0.03]
	Sig.<0	0.16	0.18	0.23	0.14
$G\_Financial_t$	q25-q75	[-0.31;0.21]	[-0.33;0.16]	[-0.14;0.23]	[0.01;0.29]
	Sig.	0.27	0.25	0.34	0.30
$G\_Macroeconomic_t$	q25-q75	[-0.21;0.28]	[-0.23;0.25]	[-0.18;0.27]	[0.07;0.31]
	Sig.	0.25	0.27	0.39	0.34
Regressions for $h = 4$					
		US financial uncertainty indicator			
y_{it}	q25-q75	[0.22;0.57]	[0.24;0.55]	[0.29;0.57]	[0.34;0.61]
	Sig.	0.61	0.70	0.89	0.98
$F\_Uncertainty_t$	q25-q75	[-0.23;0.03]	[-0.17;0.01]	[-0.11;-0.01]	[-0.1;0]
	Sig.<0	0.18	0.23	0.18	0.23
		US financial uncertainty indicator + Global factors			
y_{it}	q25-q75	[0.21;0.56]	[0.26;0.56]	[0.31;0.57]	[0.33;0.58]
	Sig.	0.59	0.75	0.89	0.98
$F\_Uncertainty_t$	q25-q75	[-0.24;-0.02]	[-0.20;0.01]	[-0.13;-0.03]	[-0.09;0.01]
	Sig.<0	0.18	0.23	0.20	0.18
$G\_Financial_t$	q25-q75	[-0.38;0.20]	[-0.26;0.25]	[-0.15;0.19]	[0.02;0.18]
	Sig.	0.27	0.20	0.27	0.23
$G\_Macroeconomic_t$	q25-q75	[-0.44;0.12]	[-0.30;0.18]	[-0.19;0.14]	[0.02;0.21]
	Sig.	0.32	0.30	0.18	0.25

Note: Sig. denotes proportion of countries for which the variable is statistically significant at 90% confidence level; q25-q75 shows the first and last quartile of the estimated coefficients. Intercepts are omitted. Standard errors are based on bootstrap with 1000 replications. Sample: 1971Q1 to 2019Q4 for 44 countries, except for Bolivia (to 2019Q3), Iceland (to 2018Q4) and Taiwan (to 2018Q4).

We observe that the impact of financial uncertainty on the lower quantiles of real credit growth is negative and higher in absolute value than on the central quantiles, although the proportion of countries for which the effect is significant, is similar across quantiles. These results hold when we control for global financial and macroeconomic factors. This time, the highest effects of financial uncertainty are recorded well in advance of h=4. Indeed, the impact is quite similar across all forecasting- horizons (h={0,1,4}). Importantly, on h=4, first moment financial shocks on credit growth (Table 1) exert an economically and statistically significant effect for a greater number of countries compared to other horizons. This is in accordance with first moment shocks associated with credit tightness and which consistently take more time to spillover to global markets, therefore supporting the credit view of the spread.

As with NFCI, we notice that the impact of financial uncertainty in the US is very heterogeneous across countries. Not only because it is a relevant predictor of negative credit dynamics for around 16-25% of our sample of countries while it is not for the rest of the economies, but also because these effects can be positive or negative. If we focus on the global factors, we observe that global factors impact heterogeneously credit creation around the world. In general, these covariates impact the average quantiles of credit growth of a higher number of countries than in the case of the negative tail. Additionally, the effects of these global factors include a wide range of values, often showing high positive values even on the lowest quantiles.

Similar to Table 2, Table 4 summarizes the estimation results for stock returns as the dependent variable but using the US financial uncertainty index instead of the NFCI as our financial conditions indicator.

Table 4: Quantile regressions, Impact of Financial Uncertainty on stock markets

		$\tau =$			
		0.05	**0.1**	**0.2**	**0.5**
Regressions for $h = 0$					
		US financial uncertainty indicator			
$F\_Uncertainty_t$	q25-q75	[-0.64;-0.36]	[-0.57;-0.30]	[-0.44;-0.23]	[-0.27;-0.16]
	Sig.<0	0.88	0.88	0.92	0.88
		US financial uncertainty indicator + Global factors			
$F\_Uncertainty_t$	q25-q75	[-0.31;-0.04]	[-0.22;-0.02]	[-0.13;-0.03]	[-0.05;0.01]
	Sig.<0	0.48	0.48	0.32	0.12
$G\_Financial_t$	q25-q75	[-0.89;-0.17]	[-0.84;-0.29]	[-0.80;-0.38]	[-0.66;-0.32]
	Sig.	0.56	0.68	0.88	0.88
$G\_Macroeconomic_t$	q25-q75	[-0.21;0.36]	[-0.15;0.24]	[-0.16;0.17]	[0.00;0.23]
	Sig.	0.28	0.28	0.36	0.4
Regressions for $h = 1$					
		US financial uncertainty indicator			
y_{it}	q25-q75	[0.09;0.45]	[0.11;0.37]	[0.18;0.33]	[0.23;0.34]
	Sig.	0.52	0.56	0.72	0.96
$F\_Uncertainty_t$	q25-q75	[-0.58;-0.33]	[-0.42;-0.26]	[-0.25;-0.12]	[-0.13;-0.02]
	Sig.<0	0.88	0.76	0.56	0.24
		US financial uncertainty indicator + Global factors			
y_{it}	q25-q75	[-0.02;0.36]	[-0.04;0.38]	[0.11;0.33]	[0.21;0.39]
	Sig.	0.32	0.32	0.60	0.72
$F\_Uncertainty_t$	q25-q75	[-0.64;-0.26]	[-0.46;-0.21]	[-0.27;-0.12]	[-0.11;-0.03]
	Sig.<0	0.6	0.76	0.6	0.24
$G\_Financial_t$	q25-q75	[-0.27;0.28]	[-0.27;0.18]	[-0.24;0.02]	[-0.24;-0.02]
	Sig.	0.20	0.20	0.16	0.12
$G\_Macroeconomic_t$	q25-q75	[-0.19;0.37]	[-0.18;0.13]	[-0.25;0.04]	[-0.18;-0.08]
	Sig.	0.20	0.04	0.08	0.16
Regressions for $h = 4$					
		US financial uncertainty indicator			
y_{it}	q25-q75	[-0.16;0.21]	[-0.05;0.12]	[-0.03;0.05]	[-0.07;0.06]
	Sig.	0.04	0.08	0.12	0.12
$F\_Uncertainty_t$	q25-q75	[-0.29;-0.09]	[-0.22;-0.08]	[-0.13;0]	[-0.04;0.04]
	Sig.<0	0.12	0.08	0.16	0.04
		US financial uncertainty indicator + Global factors			
y_{it}	q25-q75	[-0.18;0.16]	[-0.15;0.15]	[-0.11;0.06]	[-0.12;0.09]
	Sig.	0.04	0.12	0.08	0.16
$F\_Uncertainty_t$	q25-q75	[-0.27;-0.07]	[-0.19;-0.04]	[-0.11;-0.04]	[-0.08;0.00]
	Sig.<0	0.08	0.12	0.12	0.04
$G\_Financial_t$	q25-q75	[-0.48;-0.02]	[-0.50;-0.11]	[-0.42;-0.17]	[-0.40;-0.11]
	Sig.	0.12	0.16	0.52	0.64
$G\_Macroeconomic_t$	q25-q75	[-0.56;-0.09]	[-0.55;-0.08]	[-0.49;-0.22]	[-0.37;-0.25]
	Sig.	0.20	0.36	0.60	0.72

Note: Sig. denotes proportion of countries for which the variable is statistically significant at 90% confidence level; q25-q75 shows the first and last quartile of the estimated coefficients. Standard errors are based on bootstrap with 1000 replications.

Results show that at horizons h=0 and h=1, the impact of financial uncertainty at the lower tail of the distribution of conditional stock returns is very high. At horizon h=4, the effects of financial uncertainty are much less pronounced. This key result is observed even if we control for global financial and macroeconomic factors, as the percentage of countries for which the financial uncertainty coefficient is statistically significant goes from 60% (τ =0.05 quantile) to 76% (τ =0.10 quantile), out of 25 countries. This fast and strong response of global stock markets to US financial uncertainty is consistent with portfolio rebalancing by international investors following an increase of US financial uncertainty, and thus, with the portfolio view of the transmission.

As with NFCI, we observe that financial uncertainty impacts more frequently and significantly the lower quantiles of stock markets than the average quantiles while the impact of global common factors (financial and macroeconomic) is higher on the average quantiles. Interestingly, we observe a less heterogeneous response across countries than in the case of NFCI. That is, financial uncertainty is a relevant predictor of stock price declines for a larger percentage of countries than NFCI, and, in addition (in all cases), the effect documented for the lowest quartiles (τ =0.05 and τ =0.1) is negative.

Overall, our results confirm that both, first and second moment shocks to US financial conditions convey powerful signals on downside risks to funding markets. They suggest that, analogous to *vulnerable growth* episodes documented in the previous literature, there exist also *vulnerable funding* periods of a global scale, originating from financial fragility in the US. These results highlight the importance of funding for the transmission of recessionary shocks. In addition, our results emphasize the role of the portfolio view for the propagation of financial uncertainty (largely through the stock market), and of the credit view to understand the propagation of first moment financial conditions shocks (largely through the credit market). Both mechanisms are complementary and help to better understand the propagation of US financial conditions across global markets.

5.3. Cross-country heterogeneity

5.3.1. Graphical analysis

To examine which is the most likely reason for a given country vulnerability to changes in the financial conditions of the US, first, we relate the size of each country credit and stock market's responses to two classical determinants of the international spreading of financial shock, namely, the size of credit (stock) markets, and the relative importance of US foreign investment for each country. We measure the size of credit markets by the annual average of the credit to GDP ratio for each country, the size of stock markets by the annual average of the market capitalization to GDP ratio and, financial interconnection by the total direct investment of the US as a percentage of the country's GDP. To this end, we compute for each country the maximum value of US investment inflows relative to its GDP[12].

In both cases, credit and stock markets, we show the results for the horizon and the ordering measure that provides the clearest pattern. This translates into showing the results for horizon h=0 and sorting the countries by the size or depth of the market in the case of credit markets and by its financial closeness to the US in the case of stock markets[13].

Figure 2 shows the impact of NFCI over the entire distribution of credit growth of the countries in the sample (for forecasting- horizon h=0), ordered according to their credit to GDP ratio. Interestingly, we find that there is a cluster in the lower left-hand corner of the heat map, suggesting that the economies with lower credit to GDP ratios are more sensitive to a first moment shock to US financial conditions and that the response is stronger in the left tail (lower quantiles) of the distribution. However, the response of economies with higher credit to GDP ratios is much weaker, or inexistent. This is, the smaller the credit market, the most likely that country will experience vulnerable funding episodes. In turn, credit market size is associated with market development, which suggest an asymmetric impact of financial conditions first moment shocks on emerging and advanced economies This result suggest that when we focus on shocks to the first moment of the financial conditions, vulnerable funding is clearly associated with the size or depth of a country's credit market and it is consistent with the view advanced for instance by Alfaro et al. (2004) and Kalemli-Özcan (2019).

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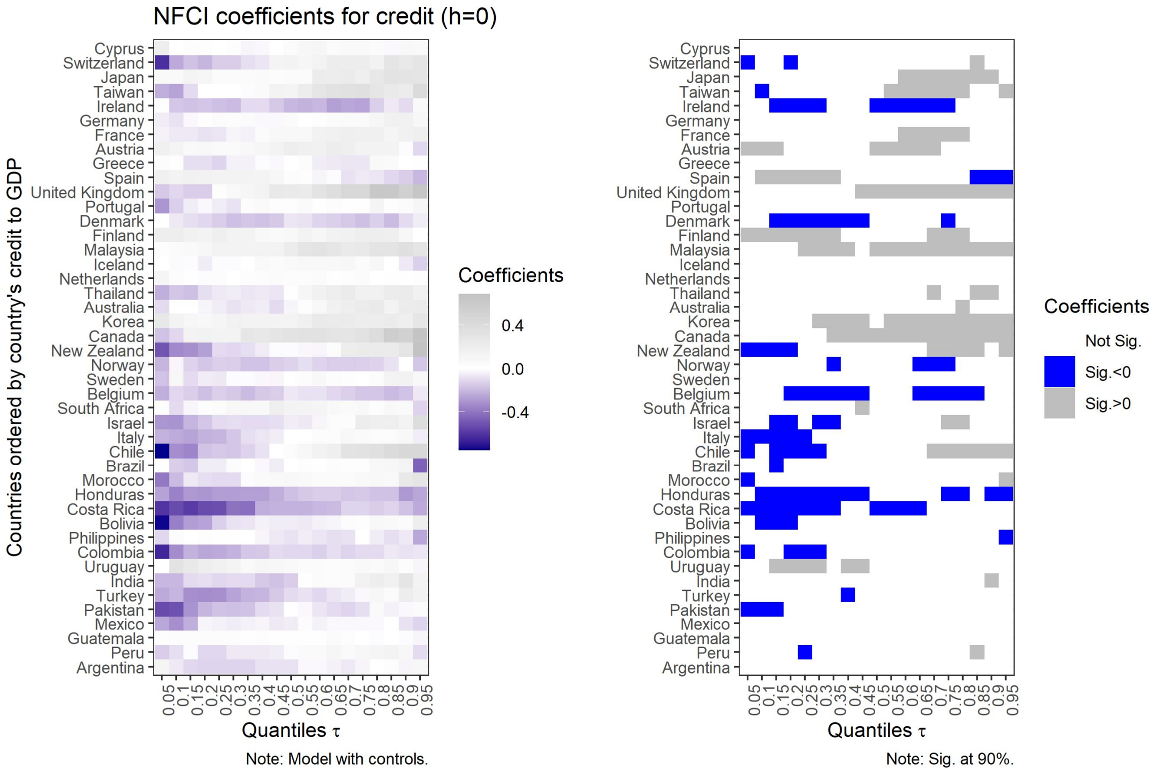
[12] Results are robust when we use the average instead of the maximum value.
[13] Results for horizons h=1 and h=4 are available upon request.

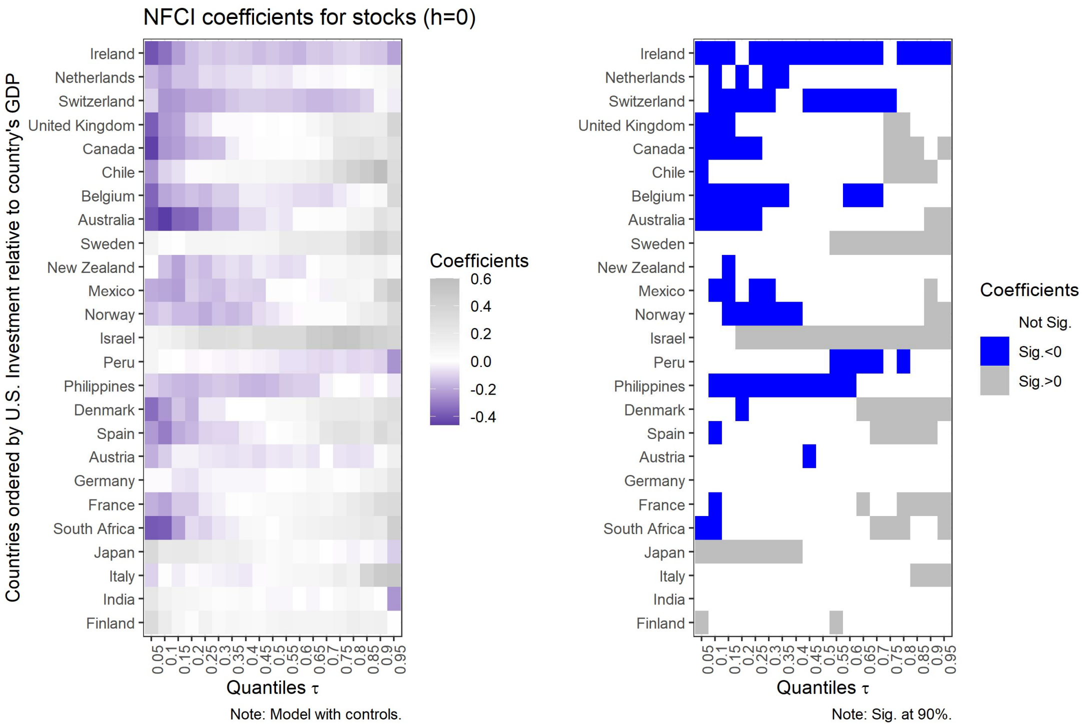
Figure 2. Impact of NFCI over the distribution of future credit growth



Note: The left-hand panel shows the NFCI coefficients for $\tau = 0.05 - 0.95$ in 0.05 intervals, for all 44 countries. The right-hand panel presents the statistically significance of the NFCI coefficients as well as the sign of the estimated coefficient. The blue (grey)-shaded areas are defined as being negative (positive) statistically significant at the 90% level of confidence, whereas the white-shaded area corresponds to insignificant coefficients associated with the NFCI.

Figure 3 shows the impact of NFCI over the entire distribution of stock returns (for forecasting- horizon *h*=0) of the countries in the sample ordered by their degree of financial interconnection with the US. We find a cluster in the upper left-hand corner of the heat maps, suggesting that the sensitivity of the effect of NFCI on the lower part of the distribution of stock returns is related to the relative importance of US investment for a given country. This fact, ultimately suggests that stock markets of economies that share stronger financial links with the US are more severely affected by a tightening in US financial conditions than economies with weaker financial ties with the US.

Figure 3. Impact of NFCI over the distribution of current stock returns



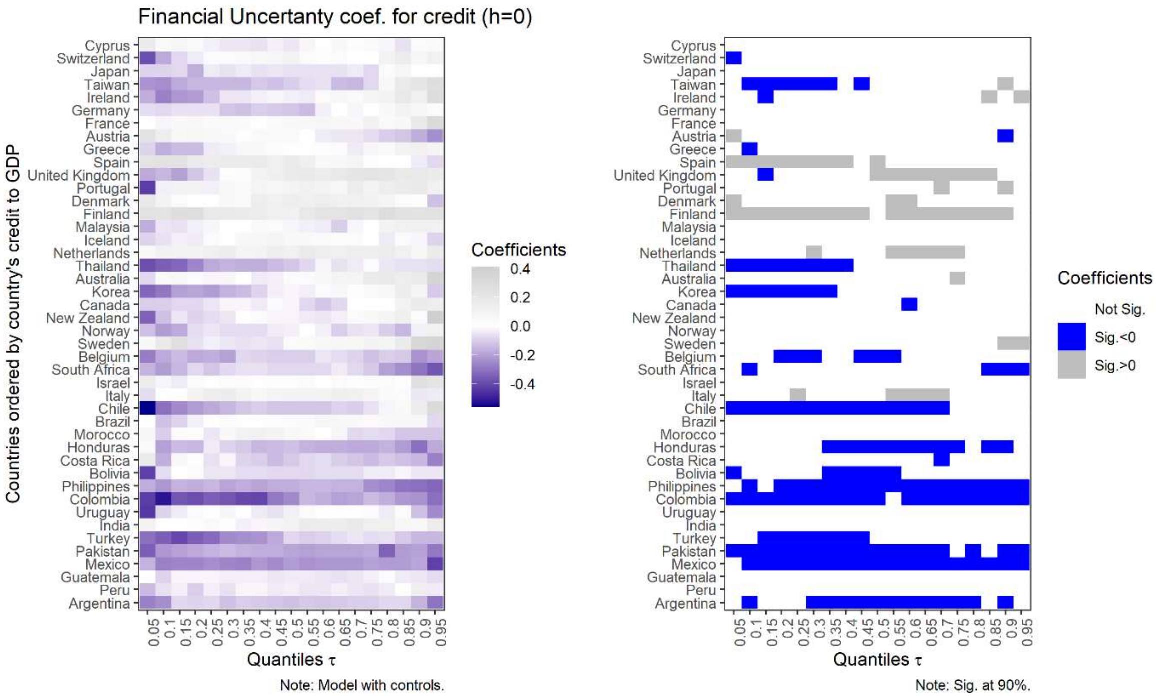
Note: The left-hand panel shows the NFCI coefficients for $\tau = 0.05 - 0.95$ in 0.05 intervals, for all 25 countries. The right-hand panel presents the statistically significance of the NFCI coefficients as well as the sign of the estimated coefficient. The blue (grey)-shaded areas are defined as being negative (positive) statistically significant at the 90% level of confidence, whereas the white-shaded area corresponds to insignificant coefficients associated with the NFCI.

Interestingly, most of the countries showing larger stock market responses to first moment shocks in US financial conditions are developed markets. It seems that the relative importance of USD foreign flows to a country does determine to a great extent how domestic share value will react following a deterioration of US financial conditions, and indeed in general, to global financial factors. While FDI flows are more volatile for emerging countries as the past literature have documented, the stock markets of advanced economies, such as Ireland, Switzerland, the Netherlands, Canada and the United Kingdom (which are the five top main receptors of US foreign direct investment), are also among the most affected countries in our sample, after a deterioration of the financial conditions in the US. This can be observed looking at the significance of the estimated effects for the five countries (right-hand side plot), and the darker color in the heat map associated to the quantile slope that measures the effect of NFCI in each market (left hand side plot) of Figure 3. Thus, the depth and liquidity of the local stock market may prevent the impact of the external shock on the real economy to be dramatic, but in any case, the local funding opportunities reduce following a deterioration of US financial conditions, as expected. These results point out to the vulnerability of local financial markets to external imbalances and credit restrictions, given the high degree of interconnectedness of current global finance.

Figure 4 shows the impact of US financial uncertainty over the entire distribution of credit growth (for forecasting- horizon *h*=0) of the countries in the sample, ordered according to size or depth of the market. As with first moment shocks to US financial conditions, we observe that the size or depth of the credit markets is important to explain credit vulnerability to financial uncertainty and that most of the countries showing higher responses are emerging market economies. Again, the smaller the credit market size, the most likely a country will experience vulnerable funding episodes. This result is consistent with Carrière-Swallow and Céspedes (2003) who find that in comparison to the U.S. and other developed countries, emerging economies suffer much more severe falls in investment and private consumption following an exogenous uncertainty shock. Bhattarai et al (2020) also document that unanticipated changes in US uncertainty have significant effects on emerging market economies.

We also find that, although in general the effect is more negative in the lower quantiles than on the central ones, the proportion of countries for which the effect is significant, is relatively similar across the entire distribution.

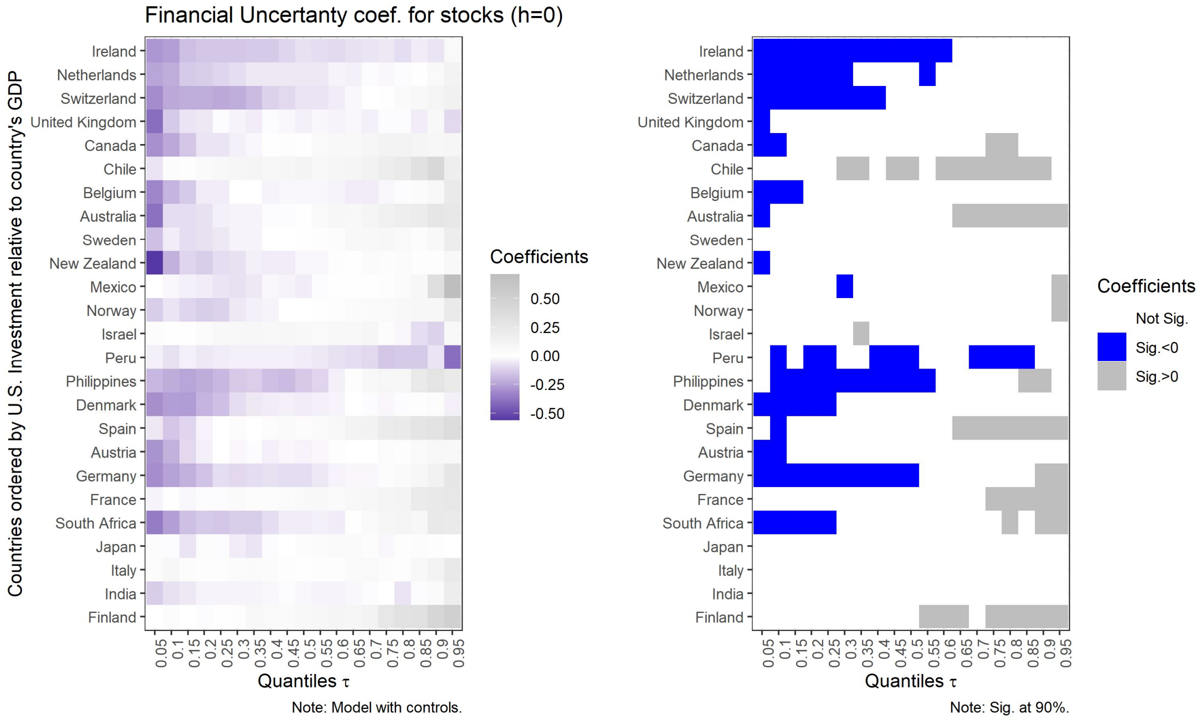
Figure 4. Impact of Financial Uncertainty index over the distribution of future credit growth



Note: The left-hand panel shows the financial uncertainty coefficients for $\tau = 0.05 - 0.95$ in 0.05 intervals, for all 44 countries. The right-hand panel presents the statistically significance of the financial uncertainty coefficients as well as the sign of the estimated coefficient. The blue (grey)-shaded areas are defined as being negative (positive) statistically significant at the 90% level of confidence, whereas the white-shaded area corresponds to insignificant coefficients associated with the financial uncertainty index.

Finally, Figure 5 shows the impact of US financial uncertainty over the entire distribution of stock return (for forecasting- horizon h=0) of the countries in the sample, ordered according to the strength of their financial links with the US. Now, we observe graphically that the impact of financial uncertainty at the left tail of the conditional distribution of stock returns is very large for a high percentage of countries. As with first moment shocks, we find a cluster in the upper left-hand corner of the heat map, suggesting that the sensitivity of the effect of financial uncertainty on the lower part of the distribution of stock returns is related to the degree of US investment abroad. Again, the stock markets of advanced economies are among the most affected countries in our sample, after a shock to financial uncertainty in the US.

Figure 5. Impact of Financial Uncertainty index over the distribution of current stock returns



Note: The left-hand panel shows the financial uncertainty coefficients for $\tau = 0.05 - 0.95$ in 0.05 intervals, for all 25 countries. The right-hand panel presents the statistically significance of the financial uncertainty coefficients as well as the sign of the estimated coefficient. The blue (grey)-shaded areas are defined as being negative (positive) statistically significant at the 90% level of confidence, whereas the white-shaded area corresponds to insignificant coefficients associated with the financial uncertainty index.

Overall, we find that the heterogeneous dynamic of Credit at Risk episodes is better explained by the size or depth of the credit market while, in the case of Equity at Risk episodes, heterogeneity is more related to the financial interconnections with the US. This result holds for both, first moment shocks and financial uncertainty shocks.

5.3.2. Cross-sectional analysis

In this subsection we present the results of our exploratory regressions that measure the association between financial vulnerability and the two classical determinants of the international spreading of financial shocks. We used as our right-hand-side variable the slope coefficients of CaR or EaR at various quantiles, and as left-hand-side variables both, the ratio of US direct investment to the GDP of each country and the ratio of credit (market capitalization) to GDP of each country. We estimate these latter variables using the average of the yearly indicators across the sample period (1960 Q1- 2019 Q4) and using the annual maximum across the sample (as to emphasize the most extreme scenarios). Table 5 to 7 present the results using the maxima version, which are virtually the same than using the averages (which are available upon request). Table 5 and 6 focus on the credit market and Table 7 and 8 on the stock market.

Table 5: Cross-sectional determinants of vulnerable credit (first moment shock)

	$\tau =$						
	0.05	0.1	0.2	0.5	0.8	0.9	0.95
Regressions for $h = 0$							
US inv./GDP (%)	0.000200	-0.000584	-0.000856	-0.00101	-0.00118*	-0.000904	0.000164
	(0.00104)	(0.000800)	(0.000615)	(0.000776)	(0.000675)	(0.000715)	(0.000798)
Credit/GDP (%)	**0.00249****	**0.00175****	**0.00144****	**0.00138*****	0.00124*	0.00120*	0.00172*
	(0.00109)	(0.000777)	(0.000584)	(0.000445)	(0.000656)	(0.000679)	(0.000911)
Constant	-0.317***	-0.213***	-0.158***	-0.0596*	0.0301	0.0330	-0.0210
	(0.0813)	(0.0615)	(0.0472)	(0.0297)	(0.0412)	(0.0493)	(0.0665)
Regressions for $h = 1$							
US inv./GDP (%)	-0.000358	-0.000884	-0.00125	**-0.000886*****	-0.000679*	-0.000343	-0.000486
	(0.000936)	(0.00112)	(0.00108)	(0.000267)	(0.000361)	(0.000879)	(0.000866)
Credit/GDP (%)	0.00193*	0.00111	0.000585	0.000496	**0.000961****	0.000534	0.00121
	(0.00102)	(0.000662)	(0.000462)	(0.000468)	(0.000431)	(0.000541)	(0.000939)
Constant	-0.280***	-0.196***	-0.126***	-0.0183	0.0192	0.0907**	0.0722
	(0.0813)	(0.0527)	(0.0304)	(0.0260)	(0.0287)	(0.0382)	(0.0625)
Regressions for $h = 4$							
US inv./GDP (%)	-0.00284	-0.00236	-0.00161*	**-0.00198*****	-0.000739	-0.00132	-0.00135
	(0.00218)	(0.00149)	(0.000853)	(0.000429)	(0.000771)	(0.00145)	(0.00108)
Credit/GDP (%)	**0.00244****	0.000960	-0.000108	**0.000800****	0.000561	-0.000139	-0.000281
	(0.00114)	(0.000755)	(0.000443)	(0.000309)	(0.000465)	(0.000621)	(0.00100)
Constant	-0.303***	-0.201***	-0.0792**	-0.0429*	0.0420	0.142***	0.160**
	(0.0935)	(0.0661)	(0.0376)	(0.0239)	(0.0281)	(0.0444)	(0.0630)
N	44	44	44	44	44	44	44

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

From a general reading of Table 5 when h=0, we have that market size significantly explains the transmission of NFCI shocks. The effect is the one expected from the theory and in accordance to previous studies, namely, the larger the market the lower the negative effect of US financial conditions on that market. When h=1, 4 market size loses its significance in most of the cases as it only remains significant at the lowest quantiles (0.05) and the median of the distribution. On its side, financial closeness to the US helps to explain the central quantiles when h=1 ($\boldsymbol{\tau} = 0.8$) and h=4 ($\boldsymbol{\tau} = 0.5$) but not the vulnerable funding episodes associated with the lowest quantiles. The same narrative suits Table 6, namely market size helps to explain the propagation of financial uncertainty across the world credit markets, when h=0, while at other horizons and especially for the lowest quantiles the explanation escapes from these two traditional determinants.

Table 6: Cross-sectional determinants of vulnerable credit (second moment shock)

	$\boldsymbol{\tau} =$						
	0.05	0.1	0.2	0.5	0.8	0.9	0.95
Regressions for $\boldsymbol{h} = \mathbf{0}$							
US inv./GDP (%)	-0.000269	-0.000502	-0.000436	0.000299	0.000801*	0.000584*	**0.00170*****
	(0.000905)	(0.00123)	(0.000972)	(0.000582)	(0.000430)	(0.000324)	(0.000410)
Credit/GDP (%)	0.00138	**0.00146****	**0.000987****	0.000936*	**0.00140****	**0.00178****	**0.00242****
	(0.000837)	(0.000549)	(0.000487)	(0.000536)	(0.000642)	(0.000797)	(0.000962)
Constant	-0.206***	-0.193***	-0.124***	-0.0844**	-0.104**	-0.118**	-0.177***
	(0.0601)	(0.0390)	(0.0362)	(0.0341)	(0.0423)	(0.0524)	(0.0643)
Regressions for $\boldsymbol{h} = \mathbf{1}$							
US inv./GDP (%)	-0.00177	-0.000651	-0.000769	0.0000613	0.000471*	**0.000766****	0.000461
	(0.00183)	(0.000984)	(0.000751)	(0.000478)	(0.000267)	(0.000347)	(0.00139)
Credit/GDP (%)	-0.000280	0.000302	0.000504	0.000586	0.000659	0.00110	0.00250*
	(0.000923)	(0.000491)	(0.000419)	(0.000401)	(0.000538)	(0.000714)	(0.00127)
Constant	-0.0672	-0.0713*	-0.0756**	-0.0572*	-0.0366	-0.0585	-0.148**
	(0.0841)	(0.0398)	(0.0353)	(0.0293)	(0.0341)	(0.0487)	(0.0724)
Regressions for $\boldsymbol{h} = \mathbf{4}$							
US inv./GDP (%)	-0.000462	-0.00135	**-0.00109****	**-0.00110*****	0.000539*	0.000190	0.000662
	(0.00141)	(0.000864)	(0.000507)	(0.000380)	(0.000294)	(0.000447)	(0.000554)
Credit/GDP (%)	0.00103	-0.000441	**-0.000644****	0.000369	0.000225	0.000322	0.0000929
	(0.000758)	(0.000510)	(0.000258)	(0.000285)	(0.000615)	(0.000780)	(0.00118)
Constant	-0.192***	-0.0627*	-0.0249	-0.0482**	-0.00561	0.0371	0.0458
	(0.0501)	(0.0353)	(0.0186)	(0.0180)	(0.0342)	(0.0466)	(0.0801)
N	44	44	44	44	44	44	44

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When we turn our attention to the stock markets, a different landscape emerges. In Table 7 we can observe that when h=0 the relative size of US investment (market closeness to the US) significantly explains the transmission of NFCI shocks. The effect is the one expected from the theory: the closest markets to the US (i.e. larger relative reception of US annual investment as a percentage of local GDP) are the most affected (independently on the size of the market), which can be rationalized with the portfolio view operating on the global transmission of US financial conditions. This time the size of the market does not offer explanatory power for the vulnerable funding episodes (or even for the transmission on the highest quantiles).

Table 7: Cross-sectional determinants of vulnerable equity (first moment shock)

	$\tau =$						
	0.05	0.1	0.2	0.5	0.8	0.9	0.95
Regressions for $h = 0$							
US inv./GDP (%)	**-0.00206****	**-0.00172*****	**-0.000933****	**-0.00102*****	**-0.00154*****	**-0.00205*****	-0.00208*
	(0.000889)	(0.000542)	(0.000361)	(0.000255)	(0.000337)	(0.000592)	(0.00107)
Market Cap./GDP (%)	-0.00124	-0.00129*	-0.000317	-0.000117	0.000412	0.000103	0.000128
	(0.00106)	(0.000713)	(0.000415)	(0.000366)	(0.000887)	(0.000773)	(0.00121)
Constant	-0.00952	-0.0128	-0.0351	0.0324	0.117*	0.217***	0.216**
	(0.0766)	(0.0554)	(0.0395)	(0.0360)	(0.0647)	(0.0650)	(0.0906)
Regressions for $h = 1$							
US inv./GDP (%)	-0.000509	-0.0000444	**-0.000627****	**-0.000906*****	**-0.000740****	-0.0000370	0.000994
	(0.000816)	(0.000462)	(0.000225)	(0.000246)	(0.000342)	(0.000395)	(0.00106)
Market Cap./GDP (%)	-0.00144	-0.000531	**-0.000890****	-0.0000682	0.00182*	**0.00275*****	**0.00237*****
	(0.00119)	(0.000933)	(0.000424)	(0.000437)	(0.000888)	(0.000791)	(0.000772)
Constant	-0.0116	-0.0382	-0.00695	-0.00529	-0.0441	-0.0617	-0.0108
	(0.1000)	(0.0714)	(0.0371)	(0.0354)	(0.0579)	(0.0676)	(0.0705)
Regressions for $h = 4$							
US inv./GDP (%)	-0.000400	-0.000130	**-0.00130*****	-0.000229	**-0.000937****	-0.0000656	-0.000329
	(0.00177)	(0.000544)	(0.000434)	(0.000495)	(0.000375)	(0.000623)	(0.000711)
Market Cap./GDP (%)	-0.00199	**-0.00240****	**-0.00145****	-0.000563	0.0000627	0.00117	0.000862
	(0.00127)	(0.000895)	(0.000611)	(0.000483)	(0.000817)	(0.00118)	(0.00114)
Constant	0.178	0.167*	0.122**	0.0469	0.0791	0.0915	0.205**
	(0.109)	(0.0869)	(0.0533)	(0.0516)	(0.0725)	(0.0748)	(0.0850)
N	25	25	25	25	25	25	25

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When we move from h=0 to h=1, 4, financial closeness keeps its explanatory power for the central quantiles but not for the lowest. Moreover, for the central cases the market size gains some statistical power, which nevertheless is accompanied by a negative sign, meaning that advanced economies are more susceptible to receive shocks from the US than emerging economies. A very similar panorama arises when we move to the last table of our estimations (Table 8). This table focuses on the second moment shocks (financial uncertainty) effect on the stock markets. Again it is financial closeness instead of market size which offers significant explanatory power of vulnerable funding episodes. The size of the stock market only matters four quarters after the shock has occurred.

All in all, our cross-sectional regressions tell us that market size and financial closeness to the US explain vulnerable funding episodes, at least contemporaneously. Nevertheless, the explanation depends on the market. Credit markets react according to market size, while stock markets to financial closeness. There are not notable differences in this case between the explanatory power of first and second moment shocks of these two variables.

Table 8: Cross-sectional determinants of vulnerable equity (second moment shock)

	$\tau =$						
	0.05	0.1	0.2	0.5	0.8	0.9	0.95
Regressions for $h = 0$							
US inv./GDP (%)	**-0.00109****	**-0.00124*****	**-0.000714*****	**-0.000578*****	**-0.00108*****	**-0.00147*****	**-0.00102****
	(0.000431)	(0.000277)	(0.000191)	(0.000140)	(0.000294)	(0.000414)	(0.000486)
Market Cap./GDP (%)	-0.00103	-0.000489	-0.000257	0.0000940	**0.000817****	0.000897	-0.000184
	(0.000684)	(0.000605)	(0.000444)	(0.000326)	(0.000373)	(0.000591)	(0.00102)
Constant	-0.107	-0.0684	-0.0467	-0.00853	0.0265	0.105*	0.201*
	(0.0678)	(0.0489)	(0.0331)	(0.0223)	(0.0326)	(0.0547)	(0.104)
Regressions for $h = 1$							
US inv./GDP (%)	**-0.00316****	**-0.00142*****	**-0.000857***	-0.000213	-0.000283	0.000396	0.0000253
	(0.00130)	(0.000404)	(0.000437)	(0.000176)	(0.000185)	(0.000346)	(0.000389)
Market Cap./GDP (%)	-0.00195*	-0.000895	-0.000746*	-0.000278	0.000753*	0.00162***	0.00126
	(0.00100)	(0.000730)	(0.000389)	(0.000397)	(0.000379)	(0.000528)	(0.000753)
Constant	-0.271***	-0.248***	-0.124***	-0.0477*	-0.0195	-0.0333	0.0816
	(0.0795)	(0.0590)	(0.0367)	(0.0264)	(0.0285)	(0.0360)	(0.0595)
Regressions for $h = 4$							
US inv./GDP (%)	0.000271	0.000310	-0.000418*	-0.000448	-0.000262	-0.000353	0.000387
	(0.000509)	(0.000283)	(0.000202)	(0.000327)	(0.000412)	(0.000330)	(0.000549)
Market Cap./GDP (%)	**-0.00212*****	**-0.00166****	-0.000471	-0.000232	0.000436	0.00112	0.00136
	(0.000677)	(0.000681)	(0.000495)	(0.000299)	(0.000448)	(0.000904)	(0.00114)
Constant	-0.0346	-0.0297	-0.0368	-0.00249	0.00279	0.00531	0.0163
	(0.0715)	(0.0456)	(0.0339)	(0.0253)	(0.0334)	(0.0565)	(0.0632)
N	25	25	25	25	25	25	25

Robust standard errors in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Conclusions

We systematically document vulnerable funding episodes in the world economy. That is, financial conditions in the United States have significant predictive power on the lowest quantiles of credit growth and stock market prices around the global economy. However, the established effects are very heterogeneous in several dimensions. Vulnerable funding depends on the country, the funding market, i.e., credit or stock, and the type of shock, i.e., mean-shock to financial conditions or second-moment uncertainty shock. We also show that vulnerable funding can be explained, mainly contemporaneously, by the relative market size in the case of credit markets and by the financial links with the US (measured by the total direct investment of the US as a percentage of the country's GDP) in the case of the stock market.

Our methodological approach uses quantile regressions, following the emphasis of the Growth at Risk literature, which allows us to examine the impact of financial conditions in the US in the whole conditional distributions of credit and stock market prices around the world, and hence to document the asymmetric impacts summarized before. We complement our model specification with global economic and financial factors, that we construct using a rich data set that comprises more than 40 countries, most of the time with information spanning almost six decades. Our results are robust to include both, a global macroeconomic factor and a global financial factor.

The impact of financial conditions of the United States on global stock markets is immediate, so that the strongest effects are observed in the same period of the realization of the shock. Reducing the possibility of using the indicator of financial conditions of the US as a measure of future market performance, or as an early warning indicator foreseeing future limited funding by corporations. The opposite occurs in the case of credit markets, the larger effects are observed according to our specification, one year after the origination of the shock, which means that financial conditions in the US may serve as a predicting variable of future vulnerability of domestic credit markets. These two effects put together emphasize on the importance of funding for the transmission of recessionary shocks throughout the global economy, and on the necessity of monitoring funding variables and their relationship with global financial shocks in financial stability exercises conducted by central banks and regulators around the world, on a regular basis.

The policy implications of our results are clear. We show that international funding markets are a source of persistence and amplification of financial conditions shocks across the global economy. This means that a deterioration of financial conditions in the US calls for policy actions in other economies around the world. For instance, an increase in market uncertainty that is associated with lower global liquidity and credit availability might amplify the fall in investment (and slows down economic recovery) observed after an international shock to US financial conditions. Under such scenarios it may be determinant on the side of domestic fiscal and monetary authorities, to foster internal demand, by reducing the cost of financing and providing liquidity to companies that look to invest once uncertainty has returned to its normal levels. We show that this line of reasoning is more general than the previous literature has indicated, because the deterioration of funding opportunities either via credit or the stock market is observed in all types of economies, regardless of the side of their financial markets. Indeed such differentiation does not matter at all for stock markets, and although it is important for credit markets, in the sense that larger markets are less prone to vulnerable funding episodes than smaller markets, vulnerable funding continues to be a concern for developed economies as well, according to our estimation results.

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Appendix

Table A1: Availability of information for each country and variable in Monnet and Puy (2019) macro-financial dataset.

Country	Variable	Start	End	T
Argentina	CPI	1950 Q1	2019 Q4	280
Argentina	Real credit	1950 Q1	2019 Q4	280
Argentina	Real GDP	1957 Q1	2019 Q4	252
Australia	CPI	1950 Q1	2019 Q4	280
Australia	Real credit	1950 Q1	2019 Q4	280
Australia	Real GDP	1957 Q1	2019 Q4	252
Australia	Nominal stock prices	1950 Q1	2019 Q4	280
Australia	Bond Yield	1955 Q1	2019 Q4	260
Austria	CPI	1950 Q1	2019 Q4	280
Austria	Real credit	1950 Q1	2019 Q4	280
Austria	Real GDP	1950 Q1	2019 Q4	280
Austria	Nominal stock prices	1950 Q1	2019 Q4	280
Belgium	CPI	1950 Q1	2019 Q4	280
Belgium	Real credit	1950 Q4	2019 Q4	277
Belgium	Real GDP	1950 Q1	2019 Q4	280
Belgium	Nominal stock prices	1951 Q1	2019 Q4	276
Belgium	Bond Yield	1957 Q1	2017 Q4	244
Bolivia	CPI	1950 Q4	2019 Q4	277
Bolivia	Real credit	1950 Q4	2019 Q3	276
Brazil	CPI	1950 Q4	2019 Q4	277
Brazil	Real credit	1950 Q4	2019 Q4	277
Brazil	Real GDP	1957 Q1	2019 Q4	252
Canada	CPI	1950 Q1	2019 Q4	280
Canada	Real credit	1950 Q1	2019 Q4	280
Canada	Real GDP	1950 Q1	2019 Q4	280
Canada	Nominal stock prices	1950 Q1	2019 Q4	280
Canada	Bond Yield	1950 Q1	2017 Q2	270
Chile	CPI	1950 Q1	2019 Q4	280
Chile	Real credit	1950 Q4	2019 Q4	277
Chile	Real GDP	1950 Q1	2019 Q4	280
Chile	Nominal stock prices	1953 Q1	2019 Q4	268
Colombia	CPI	1952 Q4	2019 Q4	269
Colombia	Real credit	1952 Q4	2019 Q4	269
Costa Rica	CPI	1950 Q4	2019 Q4	277
Costa Rica	Real credit	1950 Q4	2019 Q4	277
Cyprus	CPI	1957 Q1	2019 Q4	252
Cyprus	Real credit	1958 Q1	2019 Q4	248
Denmark	CPI	1950 Q1	2019 Q4	280
Denmark	Real credit	1950 Q1	2019 Q4	280
Denmark	Real GDP	1950 Q1	2019 Q4	280
Denmark	Nominal stock prices	1950 Q1	2019 Q4	280
Denmark	Bond Yield	1955 Q1	2019 Q4	260

El Salvador	CPI	1957 Q1	2019 Q4	252
Finland	CPI	1950 Q1	2019 Q4	280
Finland	Real credit	1950 Q4	2019 Q4	277
Finland	Real GDP	1950 Q1	2019 Q4	280
Finland	Nominal stock prices	1951 Q1	2019 Q4	276
France	CPI	1950 Q1	2019 Q4	280
France	Real credit	1950 Q1	2019 Q4	280
France	Real GDP	1950 Q1	2019 Q4	280
France	Nominal stock prices	1950 Q1	2019 Q4	280
France	Bond Yield	1955 Q1	2017 Q2	250
Germany	CPI	1950 Q1	2019 Q4	280
Germany	Real credit	1950 Q1	2019 Q4	280
Germany	Real GDP	1950 Q1	2019 Q4	280
Germany	Nominal stock prices	1953 Q1	2019 Q4	268
Germany	Bond Yield	1957 Q1	2017 Q2	242
Greece	CPI	1950 Q1	2019 Q4	280
Greece	Real credit	1953 Q4	2019 Q4	265
Greece	Real GDP	1950 Q2	2019 Q4	279
Guatemala	CPI	1950 Q1	2019 Q4	280
Guatemala	Real credit	1950 Q4	2019 Q4	277
Honduras	CPI	1950 Q4	2019 Q4	277
Honduras	Real credit	1950 Q4	2019 Q4	277
Iceland	CPI	1955 Q1	2019 Q4	260
Iceland	Real credit	1955 Q1	2018 Q4	256
Iceland	Real GDP	1957 Q2	2019 Q4	251
India	CPI	1950 Q1	2019 Q4	280
India	Real credit	1950 Q1	2019 Q4	280
India	Real GDP	1950 Q1	2019 Q4	280
India	Nominal stock prices	1950 Q1	2019 Q4	280
Ireland	CPI	1950 Q1	2019 Q4	280
Ireland	Real credit	1950 Q1	2019 Q4	280
Ireland	Real GDP	1950 Q1	2019 Q4	280
Ireland	Nominal stock prices	1955 Q1	2019 Q4	260
Ireland	Bond Yield	1957 Q1	2017 Q2	242
Israel	CPI	1951 Q4	2019 Q4	273
Israel	Real credit	1951 Q4	2019 Q4	273
Israel	Real GDP	1957 Q1	2019 Q4	252
Israel	Nominal stock prices	1955 Q1	2019 Q4	260
Italy	CPI	1950 Q1	2019 Q4	280
Italy	Real credit	1950 Q1	2019 Q4	280
Italy	Real GDP	1950 Q1	2019 Q4	280
Italy	Nominal stock prices	1950 Q1	2019 Q4	280
Italy	Bond Yield	1955 Q1	2019 Q4	260
Japan	CPI	1950 Q1	2019 Q4	280
Japan	Real credit	1950 Q1	2019 Q4	280
Japan	Real GDP	1950 Q1	2019 Q4	280
Japan	Nominal stock prices	1950 Q1	2019 Q4	280
Japan	Bond Yield	1950 Q1	2017 Q2	270

Korea	CPI	1950 Q1	2019 Q4	280
Korea	Real credit	1951 Q4	2019 Q4	273
Korea	Real GDP	1957 Q1	2019 Q4	252
Luxembourg	CPI	1950 Q1	2019 Q4	280
Luxembourg	Real GDP	1950 Q1	2019 Q4	280
Malaysia	CPI	1950 Q1	2019 Q4	280
Malaysia	Real credit	1952 Q4	2019 Q4	269
Malta	CPI	1957 Q1	2019 Q4	252
Mexico	CPI	1950 Q1	2019 Q4	280
Mexico	Real credit	1950 Q1	2019 Q4	280
Mexico	Real GDP	1950 Q1	2019 Q4	280
Mexico	Nominal stock prices	1950 Q1	2019 Q4	280
Morocco	CPI	1957 Q1	2019 Q4	252
Morocco	Real credit	1959 Q1	2019 Q4	244
Morocco	Real GDP	1957 Q1	2019 Q4	252
Netherlands	CPI	1950 Q1	2019 Q4	280
Netherlands	Real credit	1950 Q1	2019 Q4	280
Netherlands	Real GDP	1950 Q1	2019 Q4	280
Netherlands	Nominal stock prices	1950 Q1	2019 Q4	280
Netherlands	Bond Yield	1955 Q1	2019 Q2	258
New Zealand	CPI	1950 Q1	2019 Q4	280
New Zealand	Real credit	1950 Q1	2019 Q4	280
New Zealand	Real GDP	1957 Q1	2019 Q4	252
New Zealand	Nominal stock prices	1950 Q1	2019 Q4	280
New Zealand	Bond Yield	1957 Q1	2019 Q4	252
Norway	CPI	1950 Q1	2019 Q4	280
Norway	Real credit	1950 Q1	2019 Q4	280
Norway	Real GDP	1950 Q1	2019 Q4	280
Norway	Nominal stock prices	1950 Q1	2019 Q4	280
Norway	Bond Yield	1957 Q1	2019 Q4	252
Pakistan	CPI	1950 Q1	2019 Q4	280
Pakistan	Real credit	1950 Q4	2019 Q4	277
Pakistan	Real GDP	1950 Q1	2019 Q4	280
Peru	CPI	1950 Q4	2019 Q4	277
Peru	Real credit	1950 Q4	2019 Q4	277
Peru	Nominal stock prices	1950 Q1	2019 Q4	280
Philippines	CPI	1950 Q4	2019 Q4	277
Philippines	Real credit	1950 Q4	2019 Q4	277
Philippines	Real GDP	1963 Q1	2019 Q4	228
Philippines	Nominal stock prices	1953 Q1	2019 Q4	268
Portugal	CPI	1950 Q1	2019 Q4	280
Portugal	Real credit	1950 Q1	2019 Q4	280
Portugal	Real GDP	1955 Q1	2019 Q4	260
Portugal	Bond Yield	1955 Q1	2017 Q2	250
South Africa	CPI	1950 Q1	2019 Q4	280
South Africa	Real credit	1950 Q4	2019 Q4	277
South Africa	Real GDP	1957 Q1	2019 Q4	252
South Africa	Nominal stock prices	1950 Q1	2019 Q4	280

South Africa	Bond Yield	1955 Q1	2019 Q4	260
Spain	CPI	1950 Q1	2019 Q4	280
Spain	Real credit	1953 Q4	2019 Q4	265
Spain	Real GDP	1950 Q1	2019 Q4	280
Spain	Nominal stock prices	1950 Q1	2019 Q4	280
Sweden	CPI	1950 Q1	2019 Q4	280
Sweden	Real credit	1950 Q1	2019 Q4	280
Sweden	Real GDP	1950 Q1	2019 Q4	280
Sweden	Nominal stock prices	1950 Q1	2019 Q4	280
Sweden	Bond Yield	1955 Q1	2017 Q2	250
Switzerland	CPI	1950 Q1	2019 Q4	280
Switzerland	Real credit	1950 Q1	2019 Q4	280
Switzerland	Real GDP	1955 Q1	2019 Q4	260
Switzerland	Nominal stock prices	1950 Q1	2019 Q4	280
Switzerland	Bond Yield	1955 Q1	2019 Q4	260
Taiwan	CPI	1957 Q1	2019 Q4	252
Taiwan	Real credit	1957 Q1	2018 Q4	248
Taiwan	Real GDP	1957 Q1	2019 Q4	252
Thailand	CPI	1950 Q1	2019 Q4	280
Thailand	Real credit	1950 Q4	2019 Q4	277
Turkey	CPI	1950 Q4	2019 Q4	277
Turkey	Real credit	1950 Q4	2019 Q4	277
Turkey	Real GDP	1957 Q1	2019 Q4	252
United Kingdom	CPI	1950 Q1	2019 Q4	280
United Kingdom	Real credit	1950 Q1	2019 Q4	280
United Kingdom	Real GDP	1950 Q1	2019 Q4	280
United Kingdom	Nominal stock prices	1950 Q1	2019 Q4	280
United Kingdom	Bond Yield	1955 Q1	2019 Q4	260
United States	CPI	1950 Q1	2019 Q4	280
United States	Real credit	1950 Q1	2019 Q4	280
United States	Real GDP	1950 Q1	2019 Q4	280
United States	Nominal stock prices	1950 Q1	2019 Q4	280
United States	Bond Yield	1953 Q2	2019 Q4	267
Uruguay	CPI	1950 Q4	2019 Q4	277
Uruguay	Real credit	1950 Q4	2019 Q4	277
Uruguay	Real GDP	1957 Q1	2019 Q4	252

Table A2. Variables and Transformations

Original	Transformation	Definition
Real GDP ($x1_t$)	$\Delta\log(x1_t)$	Real GDP growth (q-o-q)
CPI ($x2_t$)	$\Delta^2\log(x2_t)$	Inflation growth (q-o-q)
Credit ($x3_t$)	$\Delta\log(x3_t/x2_t)$	Real credit growth (q-o-q)
Stock price ($x4_t$)	$\Delta\log(x4_t)$	Stock returns (q-o-q)
Bond yield ($x5_t$)	$\Delta(x5_t)$	Bond yield change (q-o-q)

Table A3: Descriptive statistics of the variables after transformations

Country	Variable	Mean	Sd	Min	Max
Argentina	Real credit	0.01	0.11	-0.91	0.61
Argentina	Real GDP	0.01	0.02	-0.08	0.08
Argentina	CPI	0	0.16	-1.52	0.94
Australia	Real credit	0.02	0.01	-0.02	0.06
Australia	Real GDP	0.01	0.01	-0.02	0.04
Australia	CPI	0	0.01	-0.04	0.05
Australia	Nominal stock prices	0.01	0.08	-0.49	0.2
Australia	Bond yield	-0.02	0.48	-1.65	1.83
Austria	Real credit	0.01	0.02	-0.04	0.08
Austria	Real GDP	0.01	0.01	-0.02	0.04
Austria	CPI	0	0.02	-0.13	0.08
Austria	Nominal stock prices	0.01	0.09	-0.61	0.45
Belgium	Real credit	0.01	0.02	-0.07	0.1
Belgium	Real GDP	0.01	0.01	-0.02	0.04
Belgium	CPI	0	0.01	-0.02	0.02
Belgium	Nominal stock prices	0.01	0.07	-0.37	0.21
Belgium	Bond yield	-0.02	0.34	-1.39	1.09
Bolivia	Real credit	0.02	0.1	-0.58	0.71
Bolivia	CPI	0	0.13	-1.04	0.69
Brazil	Real credit	0.02	0.07	-0.41	0.34
Brazil	Real GDP	0.01	0.02	-0.08	0.07
Brazil	CPI	0	0.11	-1.15	0.49
Canada	Real credit	0.01	0.02	-0.03	0.08
Canada	Real GDP	0.01	0.01	-0.02	0.03
Canada	CPI	0	0.01	-0.03	0.02
Canada	Nominal stock prices	0.01	0.07	-0.37	0.19
Canada	Bond yield	-0.01	0.47	-2.19	2.15
Chile	Real credit	0.03	0.08	-0.34	0.54
Chile	Real GDP	0.01	0.02	-0.14	0.11
Chile	CPI	0	0.07	-0.45	0.39
Chile	Nominal stock prices	0.07	0.16	-0.38	0.88
Colombia	Real credit	0.01	0.04	-0.19	0.13
Colombia	CPI	0	0.04	-0.22	0.22
Costa Rica	Real credit	0.01	0.04	-0.18	0.13
Costa Rica	CPI	0	0.02	-0.11	0.06
Cyprus	Real credit	0.02	0.03	-0.16	0.13
Cyprus	CPI	0	0.02	-0.06	0.05
Denmark	Real credit	0.01	0.01	-0.03	0.07
Denmark	Real GDP	0.01	0.01	-0.08	0.06
Denmark	CPI	0	0.01	-0.04	0.04
Denmark	Nominal stock prices	0.02	0.08	-0.39	0.3
Denmark	Bond yield	-0.03	0.63	-3.34	2.75
El Salvador	CPI	0	0.02	-0.05	0.05
Finland	Real credit	0.01	0.02	-0.05	0.14
Finland	Real GDP	0.01	0.01	-0.07	0.05
Finland	CPI	0	0.01	-0.04	0.04

Finland	Nominal stock prices	0.02	0.1	-0.35	0.42
France	Real credit	0.01	0.02	-0.04	0.08
France	Real GDP	0.01	0.01	-0.05	0.08
France	CPI	0	0.01	-0.02	0.01
France	Nominal stock prices	0.01	0.08	-0.33	0.23
France	Bond yield	-0.02	0.42	-1.62	1.81
Germany	Real credit	0.01	0.01	-0.02	0.05
Germany	Real GDP	0.01	0.01	-0.05	0.04
Germany	CPI	0	0.01	-0.02	0.03
Germany	Nominal stock prices	0.01	0.08	-0.32	0.23
Germany	Bond yield	-0.03	0.37	-1.37	1.07
Greece	Real credit	0.01	0.03	-0.07	0.1
Greece	Real GDP	0.01	0.02	-0.05	0.08
Greece	CPI	0	0.03	-0.07	0.07
Guatemala	Real credit	0.01	0.11	-1.44	0.58
Guatemala	CPI	0	0.02	-0.08	0.09
Honduras	Real credit	0.02	0.03	-0.1	0.12
Honduras	CPI	0	0.02	-0.06	0.05
Iceland	Real credit	0.01	0.05	-0.15	0.28
Iceland	Real GDP	0.01	0.02	-0.09	0.1
Iceland	CPI	0	0.03	-0.15	0.12
India	Real credit	0.02	0.04	-0.11	0.15
India	Real GDP	0.01	0.02	-0.07	0.09
India	CPI	0	0.03	-0.13	0.09
India	Nominal stock prices	0.02	0.11	-0.64	0.37
Ireland	Real credit	0.01	0.03	-0.1	0.11
Ireland	Real GDP	0.01	0.02	-0.06	0.21
Ireland	CPI	0	0.01	-0.07	0.04
Ireland	Nominal stock prices	0.02	0.09	-0.49	0.35
Ireland	Bond yield	-0.02	0.66	-2.19	2.4
Israel	Real credit	0.03	0.05	-0.17	0.45
Israel	Real GDP	0.01	0.02	-0.12	0.1
Israel	CPI	0	0.04	-0.3	0.23
Israel	Nominal stock prices	0.05	0.14	-0.84	0.61
Italy	Real credit	0.01	0.03	-0.05	0.09
Italy	Real GDP	0.01	0.01	-0.03	0.1
Italy	CPI	0	0.01	-0.05	0.04
Italy	Nominal stock prices	0.01	0.1	-0.3	0.35
Italy	Bond yield	-0.02	0.56	-2.3	2.34
Japan	Real credit	0.01	0.02	-0.07	0.08
Japan	Real GDP	0.01	0.01	-0.05	0.03
Japan	CPI	0	0.01	-0.04	0.05
Japan	Nominal stock prices	0.01	0.08	-0.36	0.22
Japan	Bond yield	-0.03	0.35	-1.22	1.5
Korea	Real credit	0.03	0.04	-0.13	0.19
Korea	Real GDP	0.02	0.02	-0.07	0.08
Korea	CPI	0	0.03	-0.13	0.17
Luxembourg	Real GDP	0.01	0.02	-0.05	0.06

Luxembourg	CPI	0	0.01	-0.03	0.02
Malaysia	Real credit	0.03	0.04	-0.07	0.24
Malaysia	CPI	0	0.01	-0.06	0.03
Malta	CPI	0	0.02	-0.04	0.05
Mexico	Real credit	0.01	0.06	-0.31	0.28
Mexico	Real GDP	0.01	0.02	-0.06	0.08
Mexico	CPI	0	0.03	-0.22	0.09
Mexico	Nominal stock prices	0.05	0.15	-0.72	0.7
Morocco	Real credit	0.02	0.04	-0.13	0.12
Morocco	Real GDP	0.01	0.03	-0.14	0.17
Morocco	CPI	0	0.02	-0.07	0.04
Netherlands	Real credit	0.01	0.02	-0.04	0.08
Netherlands	Real GDP	0.01	0.01	-0.05	0.06
Netherlands	CPI	0	0.01	-0.06	0.04
Netherlands	Nominal stock prices	0.01	0.08	-0.42	0.17
Netherlands	Bond yield	-0.02	0.37	-1.23	1.31
New Zealand	Real credit	0.01	0.04	-0.12	0.17
New Zealand	Real GDP	0.01	0.02	-0.08	0.11
New Zealand	CPI	0	0.01	-0.06	0.05
New Zealand	Nominal stock prices	0.01	0.08	-0.44	0.23
New Zealand	Bond yield	-0.02	0.61	-2.33	4.35
Norway	Real credit	0.01	0.02	-0.05	0.08
Norway	Real GDP	0.01	0.01	-0.03	0.04
Norway	CPI	0	0.01	-0.05	0.06
Norway	Nominal stock prices	0.02	0.1	-0.51	0.34
Norway	Bond yield	-0.01	0.37	-1.45	1.56
Pakistan	Real credit	0.02	0.06	-0.21	0.24
Pakistan	Real GDP	0.01	0.02	-0.05	0.09
Pakistan	CPI	0	0.02	-0.1	0.11
Peru	Real credit	0.02	0.08	-0.52	0.34
Peru	CPI	0	0.15	-1.56	1.23
Peru	Nominal stock prices	0.08	0.35	-0.47	3.37
Philippines	Real credit	0.02	0.05	-0.23	0.13
Philippines	Real GDP	0.02	0.11	-0.1	1.62
Philippines	CPI	0	0.03	-0.12	0.11
Philippines	Nominal stock prices	0.01	0.13	-0.36	1.09
Portugal	Real credit	0.01	0.03	-0.07	0.07
Portugal	Real GDP	0.01	0.01	-0.03	0.06
Portugal	CPI	0	0.02	-0.08	0.06
Portugal	Bond yield	0	0.72	-3.76	3.07
South Africa	Real credit	0.01	0.02	-0.04	0.09
South Africa	Real GDP	0.01	0.01	-0.02	0.05
South Africa	CPI	0	0.01	-0.04	0.03
South Africa	Nominal stock prices	0.02	0.09	-0.26	0.24
South Africa	Bond yield	0.02	0.61	-2.07	3.39
Spain	Real credit	0.01	0.02	-0.07	0.08
Spain	Real GDP	0.01	0.01	-0.03	0.04
Spain	CPI	0	0.01	-0.04	0.04

Spain	Nominal stock prices	0.01	0.09	-0.28	0.36
Sweden	Real credit	0.01	0.02	-0.06	0.06
Sweden	Real GDP	0.01	0.01	-0.04	0.03
Sweden	CPI	0	0.01	-0.04	0.03
Sweden	Nominal stock prices	0.02	0.09	-0.29	0.33
Sweden	Bond yield	-0.02	0.45	-1.76	2.06
Switzerland	Real credit	0.01	0.01	-0.05	0.05
Switzerland	Real GDP	0.01	0.01	-0.05	0.03
Switzerland	CPI	0	0.01	-0.02	0.03
Switzerland	Nominal stock prices	0.01	0.07	-0.34	0.16
Switzerland	Bond yield	-0.02	0.27	-0.82	0.87
Taiwan	Real credit	0.02	0.03	-0.14	0.12
Taiwan	Real GDP	0.02	0.02	-0.05	0.08
Taiwan	CPI	0	0.02	-0.16	0.08
Thailand	Real credit	0.02	0.03	-0.09	0.13
Thailand	CPI	0	0.02	-0.06	0.08
Turkey	Real credit	0.02	0.06	-0.25	0.18
Turkey	Real GDP	0.01	0.02	-0.11	0.07
Turkey	CPI	0	0.04	-0.2	0.14
United Kingdom	Real credit	0.01	0.02	-0.04	0.07
United Kingdom	Real GDP	0.01	0.01	-0.03	0.05
United Kingdom	CPI	0	0.01	-0.08	0.04
United Kingdom	Nominal stock prices	0.02	0.08	-0.27	0.35
United Kingdom	Bond yield	-0.02	0.54	-1.88	1.76
United States	Real credit	0.01	0.02	-0.04	0.04
United States	Real GDP	0.01	0.01	-0.02	0.04
United States	CPI	0	0.01	-0.04	0.02
United States	Nominal stock prices	0.02	0.06	-0.36	0.19
United States	Bond yield	-0.01	0.46	-2.45	1.54
Uruguay	Real credit	0	0.07	-0.31	0.22
Uruguay	Real GDP	0.01	0.02	-0.07	0.09
Uruguay	CPI	0	0.04	-0.17	0.18

Table A4. Correlations between global factors

Coefficient of correlation	Financial factor (PC1)	Financial factor (2 stage)	Macroeconomic factor (PC1)	Macroeconomic factor (2 stage)
Financial factor (PC1)	1	0.98	-0.88	-0.98
Financial factor (2 stage)	0.98	1	-0.89	-0.99
Macroeconomic factor (PC1)	-0.88	-0.89	1	0.93
Macroeconomic factor (2 stage)	-0.98	-0.99	0.93	1

Table A5. Cross-section variables

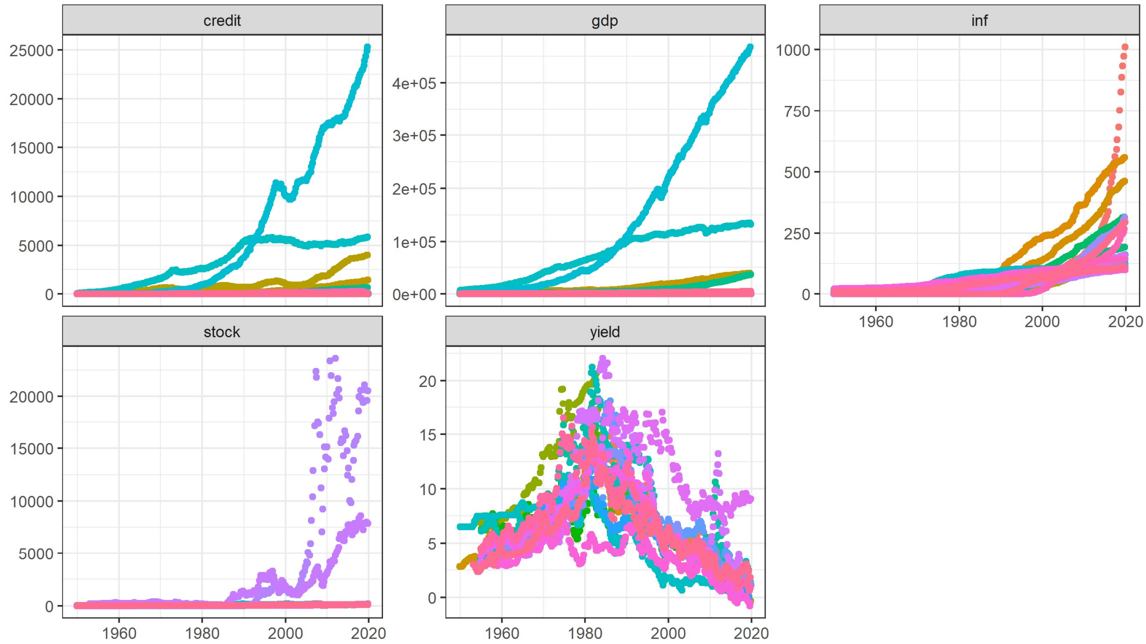
Country	Credit/ GDP (%)		Market Cap./GDP (%)		US inv./GDP (%)	
	Mean	N	Mean	N	Max	N
Argentina	16.44	58	10.86	43	10.04	31
Australia	65.1	60	79.36	41	13.25	30
Austria	90.24	19	17.74	45	4.43	31
Belgium	61.95	19	46.02	44	13.27	31
Bolivia	29.15	60			6.1	31
Brazil	41.07	60	49.3	20	6.2	31
Canada	64.04	49	108.49	41	23.26	31
Chile	44.14	60	95.97	29	14.83	31
Colombia	28.23	60	45.84	15	4.45	31
Costa Rica	30	60	6.45	18	15.21	31
Cyprus	193	19	25.72	14	23.48	30
Denmark	81.41	54	29.21	30	5.4	30
El Salvador	34.73	55			17.58	31
Finland	81.15	19	63.67	22	1.39	30
France	90.71	19	48.45	44	3.37	31
Germany	92.08	19	32.13	45	3.84	31
Greece	89.29	19	37.06	19	0.79	31
Guatemala	19.18	60			4.61	31
Honduras	30.03	60			8.61	31
Iceland	72.1	60			3.4	14
India	26.94	60	76.27	17	1.75	30
Ireland	98.38	19	51.83	22	135.64	31
Israel	52.25	60	49.75	41	7.98	31
Italy	50.44	30	45.69	10	2.05	31
Japan	119.36	60	70.48	45	2.59	31
Korea	65.03	60	47.69	40	2.63	31
Luxembourg	56.23	30	104.14	45	1095.82	31
Malaysia	78.15	60	132.34	39	7.74	31
Malta	57.2	26	43.01	20	21.5	18
Mexico	21.12	60	21.19	44	9.34	31

Morocco	31.49	56	55.38	10	0.7	31
Netherlands	71.03	30	66.59	43	111.54	31
New Zealand	63.4	60	38.94	35	10.6	31
Norway	62.94	60	40.37	39	8.5	31
Pakistan	22.24	60	21.94	24	0.96	30
Peru	18.04	60	37.78	23	7.47	31
Philippines	28.47	60	58.04	24	7.34	31
Portugal	81.5	30	23.07	42	2.3	30
Singapore	77.43	60	166.79	41	85.84	31
South Africa	52.37	59	167.8	45	2.88	31
Spain	84.2	30	48.1	44	5.37	31
Sweden	62.66	60	48.19	29	11.29	31
Switzerland	126.4	57	142.54	45	37.09	31
Taiwan					5.09	30
Thailand	70.51	60	66.1	31	5.79	31
Turkey	25.24	60	24.86	27	0.82	31
United Kingdom	83.1	60	86.3	34	30.54	31
Uruguay	27.63	60	4.06	2	5.09	30

Note: N denotes the annual non-missing sample size available for each indicator. Time spam for Credit/ GDP and Market Cap./GDP is 1960 to 2019, and for US inv./GDP is 1989 to 2019.

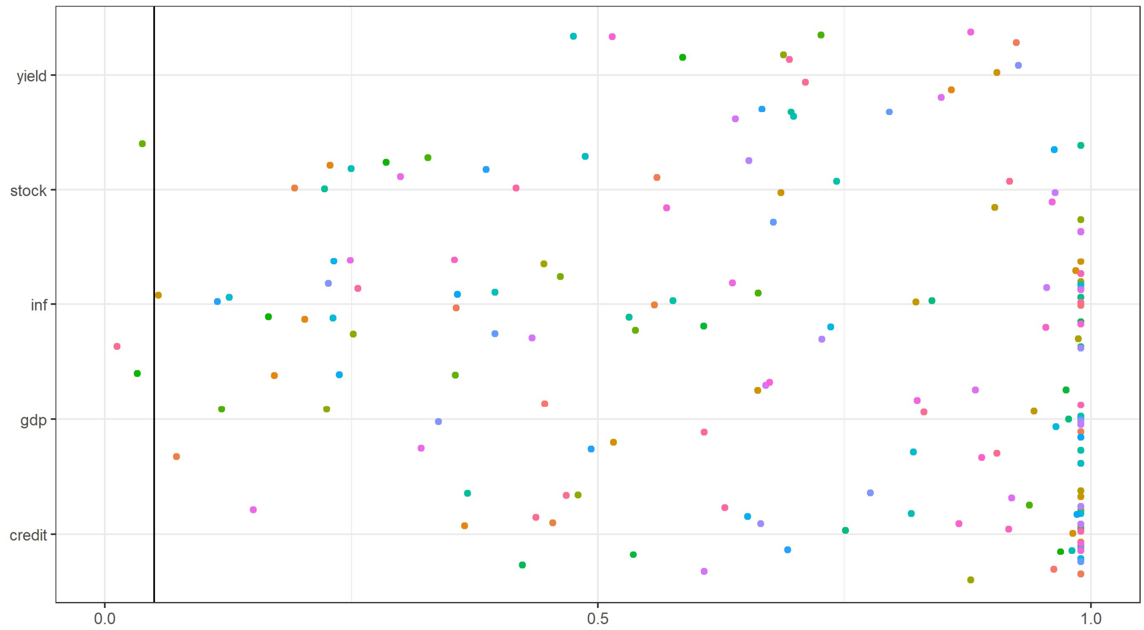
Figure A1. Original series, transformed series and unit root tests

a. Untransformed data



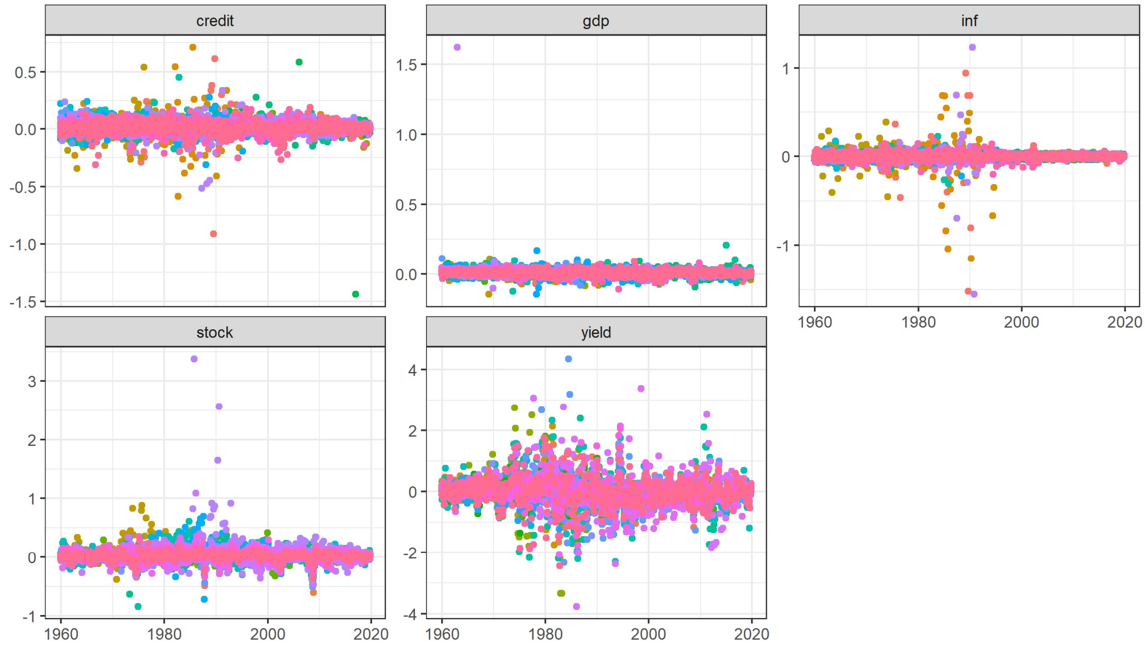
Note: each color represent a country.

b. ADF tests for untransformed data, p-value



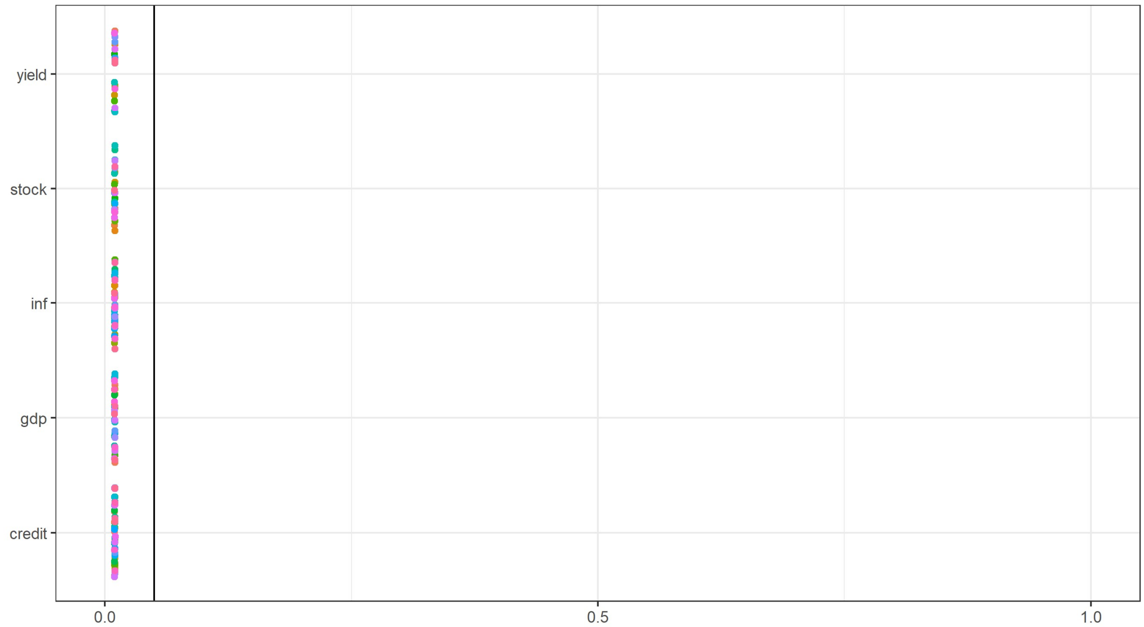
Note: each color represent a country.
We test for unit root using the ADF test by setting the maximum number of lags = 12(T/100)1/4, where T is the sample size.

c. Transformed data (1960-2019)



Note: each color represent a country.

d. ADF tests for transformed data, p-value



Note: each color represent a country.
We test for unit root using the ADF test by setting the maximum number of lags = 12(T/100)1/4, where T is the sample size.

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