The impact of risk cycles on business cycles: a historical view*

Jón Daníelsson Marcela Valenzuela Ilknur Zer

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Abstract

We investigate the effects of financial risk cycles on business cycles, using a panel spanning 73 countries since 1900. Economic agents use a Bayesian learning model to form their beliefs on whether risk is high or low. We construct a proxy of these beliefs and study their interaction with economic growth and investment behavior. The longer the agents perceive risk as low, the stronger their risk-taking behavior, initially augmenting growth but at the cost of the buildup of financial vulnerabilities and therefore, followed by a reversal in growth. The reversal is particularly pronounced when the low-for-long risk environment and credit growth are excessive. The impact of global risk cycles is much stronger than country-level risk cycles highlighting the importance of the global environment. Strengthening beliefs of global low risk affects growth amid its notable impact on capital flows, investment, and lending quality, challenging monetary policy independence, especially for emerging economies.

Keywords: Stock market volatility, uncertainty, monetary policy independence, financial instability, risk-taking, global financial cycles
JEL classification: F30, F44, G15, G18, N10, N20

*Corresponding author: Ilknur Zer. Federal Reserve Board, Washington DC, 20007, USA. ilknur.zerboudet@frb.gov. Jon Danielsson is at the London School of Economics (LSE) and the director of the Systemic Risk Centre at LSE. Marcela Valenzuela is at the School of Management, Pontificia Universidad Católica de Chile. We thank Nelson Camanho, Alessandro Rebucci, Consuelo Silva, Andreas Uthemann, and Jean-Pierre Zigrand, as well as seminar participants in the Nova School of Business and Economics, Banco de Portugal, Banque de France, Federal Reserve Board, IMF Macro-Financial Research Division, University of Cyprus, Pontificia Universidad Católica de Chile, and Adolfo Ibáñez University, and European Economic Association meetings for valuable comments. Alessandro De Trane provided excellent research assistance. We thank Stefano Giglio (the editor) and two anonymous referees. Philipp Adämmer wrote the LPIRFS R package we used in the analysis (Adämmer, 2019). The webappendix for the paper is `modelsandrisk.org/appendix/risk-cycles/`. The views in this paper are solely those of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System.

1 Introduction

The global financial crisis in 2008 reminded us of the importance of the financial sector for the macroeconomy, a lesson many had forgotten in the decades after the previous global crisis, the Great Depression. Financial risk matters. It is necessary for investment and growth but also drives uncertainty, inefficiency, recessions, and crises. While the interplay between financial risk and macroeconomy is complex, our interest in this work is on one particular dimension: how economic agents' perception of financial risk affects business cycles. We refer to the map of rises and falls in agents' perception of risk as *the risk cycle* and investigate how financial risk cycles, obtained from market prices and spanning 73 countries since 1900, affect business cycles.

While the obvious way to proceed empirically would be to simply model the impact of risk measurements on economic growth, there is an important nuance that can only be captured by separating periods of high risk from low risk. As high risk is characterized by high uncertainty, it is detrimental to economic growth, in part, because it increases the real option value of waiting on investment, encouraging firms to delay their investments (Dixit and Pindyck, 1994; Bloom, 2009; Bloom et al., 2018; Pflueger et al., 2020). If high risk is detrimental to growth, one might therefore expect low risk to be similarly beneficial. We hypothesize that it is, but only in the short run. As time passes, a reversal on the impact on growth becomes increasingly likely — what we term the boom-to-bust effect of low risk on business cycles.

While several factors might account for how low risk affects growth, we surmise that the inability to measure risk accurately and the evolution of financial leverage play a particularly large role. Risk is a latent variable, so one can only use a model to estimate it, implying all risk measurements are inaccurate. Consequently, the degree of economic agents' beliefs in the accuracy of risk measurements is of crucial importance to them. In our setting, the agent's beliefs are reinforced by them learning from repeated observations of risk being low, in the spirit of Veronesi's (1999) Bayesian learning model. In turn, the strength of the agents' beliefs reinforces optimism and willingness to take on more risk, consistent with the literature on procyclical leverage.[1] Moreover, during such tranquil periods, asset prices increase because of the fundamental value (Brunnermeier and Pedersen, 2009) or the resale value of assets (Scheinkman and Xiong, 2003). Thus, beliefs, financial frictions, and risk-taking incentives interact: willingness to take on more

[1] In Geanakoplos (2001); Fostel and Geanakoplos (2008), agents are subject to collateral constraints, which are loosened during low-risk periods. Similarly, value-at-risk constraints are loosened when volatility is low as in Brunnermeier and Pedersen (2009); Daníelsson et al. (2012). Caballero and Simsek (2020) model low and high volatility states separately and show that investors do not require high compensation to invest in low-risk states.

risk, increased asset prices, along with the easier credit conditions drive investment and hence, economic growth — the *boom* in the boom-to-bust cycle.

However, eventually, the agents start running out of high-quality investments and asset prices revert, making constraints binding (Greenwood and Hanson, 2013; Adrian and Liang, 2018). Depressed asset prices reduce the value of borrowers' assets, depressing investment as in Bernanke and Gertler (1989); Bernanke et al. (1999) and laying the seeds for a reversal, along the lines of Minsky's (1977) instability hypothesis — the *bust* in the boom-to-bust cycle.

We further expect that the strength of the boom-to-bust cycle and the aggregate impact of low-risk perceptions on economic growth depends on the underlying credit market conditions and the length of the low-risk periods. When credit growth is "excessive", the financial system is more likely to be in a vulnerable state (see for example Schularick and Taylor, 2012; Aikman et al., 2017). Increased risk-taking—fueled by a longer-lasting low-risk environment—boosts the amplitude of the bust cycle because, in that case, even a small revision of beliefs can create a self-reinforcing feedback loop that impairs credit provision, lowers asset prices, and depresses economic activity.

There is a strong global dimension in the impact of risk perceptions on growth and financial stability, stressed in the recent literature on global financial cycles (see e.g. Di Giovanni et al., 2021; Miranda-Agrippino and Rey, 2020; Rey, 2018; Jordà et al., 2018; Durdu et al., 2020). Both global and domestic investors are guided by perceptions of global risk when raising funds in global capital markets and how they allocate those funds to investments. We then propose three channels for how global risk perceptions affect growth: via domestic investment, international capital flows, and debt-issuer quality. When investors perceive risk as low globally, they seek riskier investment alternatives and are more inclined to reach for yield by allocating funds to riskier asset classes and countries, boosting capital flows (see e.g., Bruno and Shin, 2015). Easing in global financial conditions transmit to domestic credit conditions and increase local lending and investment (Di Giovanni et al., 2021). Moreover, in such periods of heightened risk-taking, even poor quality borrowers are more likely to be financed (Greenwood and Hanson, 2013), further boosting short-term growth, at the cost of increased financial vulnerabilities. Thus, we expect a similar boom-to-bust cycle in investment, capital flows, and debt-issuer quality.

This paper has three methodological contributions. First, we construct a model of agents' beliefs in the accuracy of risk measurements, that is, their posterior probability of risk being low or high. The second contribution is an empirical model of risk perceptions based on a proxy for the posterior belief, what we term the duration of low risk, or DLR. We estimate DLR with stock market returns for various countries in a long time-series, giving us a broad historical and international perspective on the nexus between financial risk and business cycles. Moreover, that approach enables us to examine whether risk perceptions in stock markets are an important driver of economic fluctuations. Our final methodological contribution is to create a measure of global risk perception, global DLR (G-DLR), by aggregating the DLR estimates across each country in our sample. As both DLR and G-DLR affect agents' willingness to assume risk, the rises and falls in DLR and G-DLR form the domestic and global risk cycles, respectively. We use G-DLR to study the relative importance of global and local risk cycles on country-specific business cycles.

We start our analysis with a model of risk beliefs. Suppose the stochastic model governing market volatility contains a persistent Markov switching mean component that determines whether the volatility state is high or low. While the actual state is latent, the agents receive a noisy signal of it, which they combine with their prior belief of the risk state to construct a posterior belief of whether risk is low or high. The strength of the agents' beliefs in the validity of a risk measurement—their posterior beliefs—drives their appetite for risk, and hence, their investment decisions. While we cannot directly estimate the agent's posterior beliefs, we know its characteristics and can therefore propose a proxy, DLR, which is highly correlated with the posterior. By construction, DLR increases at a decreasing rate along with the length of a low-risk environment.

To estimate DLR, we need to quantify what "low risk" is. To this end, we measure risk by realized stock market volatility[2] and calculate its trend, so that an agent receives a low signal if estimated volatility is below its trend in a given year. Thus, we use the historical volatility trend as the proxy of "usual" risk, and implicitly assume that agents alter their investment decisions when risk deviates from such levels, as in Keynes' (1936) animal spirits. To estimate the trend, similar to our earlier work (Danielsson, Valenzuela, and Zer, 2018), we use a one-sided Hodrick-Prescott (1997) filter using only past information to estimate the trend for a given time, necessary in our case because we run predictive regressions.[3]

As a prelude to our empirical analysis, we confirm that DLR is closely related to other measures of investor risk perception and risk appetite, including the measures based on option prices and survey-based expectations of corporate credit conditions. In addition, in a panel regression setting, we show that DLR is significantly correlated with contemporaneous stock market returns: lower perceived risk is associated with an increase in the prices of risky assets. Finally, DLR rises

[2] Alternatively, we could have used corporate bond spread data since spreads are especially informative about credit conditions and the real macroeconomic outcomes (Gilchrist et al., 2009). However, country-level historical cross-sectional data on bond spreads are scarce. Moreover, traditional rational asset pricing models, including Bansal and Yaron (2004) suggest that stock prices are forward-looking and thus the agents' risk appetite should be reflected in the aggregate stock market prices (Pflueger et al., 2020).

[3] In Section 4, we show that our main findings do not change when employing the linear projection method proposed by Hamilton (2018).

(risk perceptions fall) with the arrival of good macroeconomic news, low macroeconomic uncertainty, excess financial market liquidity, and looser than expected monetary policy decisions.

Our empirical framework is impulse response functions obtained from Jordà's (2005) local projection method, which captures the impact of the one-year increase in the persistence of low or high risk on growth, contemporaneously and up to five years into the future. We find six sets of results:

First, a positive shock to DHR — risk remaining high for an additional year — has an unambiguous negative impact on economic growth, contemporaneously and in the next year. A one standard deviation increase in local DHR decreases economic growth by 0.8% cumulatively, whereas the economic impact of global DHR is about double of its local counterpart, with a cumulative contraction of 1.4%. These results are in line with the extant literature, which associates high volatility with high uncertainty, harming growth, and emphasizes the importance of global financial factors (e.g., Bloom, 2009; Rey, 2018).

Second, the impact of perceptions of risk being low is not merely the mirror opposite of its high-risk counterpart. Instead, a positive shock to DLR has a boom-to-bust impact on economic growth: Growth increases contemporaneously and especially one year hence, with a significant reversal in year two. The impact of global DLR is about double of the local counterpart. Even with a correction in year two, a one standard deviation increase in global DLR increases economic growth by 0.8% across the boom-to-bust cycle. Thus, a low-risk environment has a cumulative positive impact on GDP growth.

In the third set of results, however, we show that the cumulative impact of low risk on growth might be negative overall: when the low risk has persisted for a particularly long time and when a country experiences a credit boom. The marginal impact of G-DLR on growth is concave: initially increasingly positive, but then turning negative. That is, a very-long low-risk environment this year leads to a decrease in cumulative growth over its boom to bust cycle. Moreover, if a country is in the highest decile of credit growth in a particular year, the amplitude of the bust cycle is triple what it would otherwise be and longer-lasting. In particular, in that case, a shock to global DLR translates into a 0.65% contraction on growth over the boom-to-bust cycle cumulatively. Thus, we conclude that if a country experiences "excessive" credit growth or if a low-for-long risk period persists, strengthening perceived low risk globally further exacerbates financial vulnerabilities, making the economy more fragile, further reducing growth on aggregate. The 2008 crisis illustrates these findings well. DLR was particularly low in the years before the crisis, while credit growth was excessive, suggesting that the overall boom-to-bust effect had a negative impact on growth. Taken together, these results provide support for our notion of financial vulnerability-driven economic contraction.

While we find an unambiguous boom-to-bust effect of perceived low risk on growth, the results might be biased by endogeneity. An omitted variable can affect both the risk perceptions and growth or the causality may go from growth to volatility but not in the opposite direction. We attempt to address these concerns with two approaches. First, similar to López-Salido et al. (2017), we employ a two-stage regression analysis. In the first stage, we regress G-DLR on a range of plausibly exogenous variables (including natural disasters, terrorist attacks, political and liquidity shocks) that can affect agents' perceptions of risk. In the second stage, we investigate the effects of the fitted values of G-DLR on growth. Second, we use the news shocks of Berger et al. (2020), derived from option prices and orthogonal to current realized volatility innovations. Our results continue to hold when we use either approach. We do not make strong identification claims as the instruments are not likely to satisfy the exclusion restrictions that are required in an instrumental variable estimation. Still, the two exercises increase our confidence in the validity of our results that an increase in G-DLR leads to a boom-to-bust cycle. Moreover, our main findings are robust to a range of alternative specifications and parameterizations, including alternative definitions of volatility, volatility trend, and model specifications.

Fourth, we examine three channels for how perceived low risk affects growth: domestic investment, capital flows, and debt-issuer quality (measured by the share of high yield bond issuance). We find that a positive global DLR shock has a significant and strong impact on domestic investment, portfolio capital flows, and the share of high yield bond issuance: initially positive, but turning negative in years two to four. Moreover, we find that the effects of local DLR on investment, capital flows, and debt-issuer quality are negligible.

Fifth, because of the way G-DLR is constructed, we can add further nuance to the emerging literature on the importance of the United States for global financial cycles. We repeat our impulse response analysis, but this time replace G-DLR with the local U.S. DLR. We find supporting evidence that the United States plays a pivotal role in shaping the global risk cycles. We find that US-DLR explains about 30% of the variation in G-DLR, with a large impact on country-level growth, yet weaker than that of G-DLR.

Finally, by splitting the sample into countries classified by the IMF as developed or emerging, we find that the effects of global risk cycles on emerging countries' growth is higher than that of the local risk cycles and developed countries.

Taken together, we show that perception of high-risk has an unambiguous negative impact on growth, while low risk has an initial positive and then negative impact. A strengthening perception of risk being low has an overall positive impact on growth, except in times of very high credit growth, when the supply of high-quality assets is likely to be diminished. The global risk environment is particularly important in shaping local business cycles through its effects on investment, capital flows, and debt-issuer quality.

Our results contribute to several important policy debates, including macroprudential regulations, monetary policy independence, and the importance of the global risk environment. Policymakers should consider the joint impact of global risk perceptions, above and beyond local risk, and macroeconomic outcomes. Even if a domestic monetary authority intends to either stimulate or cool down its national economy by affecting the price and quantity of money, global risk perceptions and risk-taking incentives in global financial markets (or a central economy like the United States) can override national monetary policy decisions.

Our paper relates to several branches of the literature. First, Kozlowski et al. (2020) model how agents form their beliefs, enabling tail events to trigger larger belief revisions. Meanwhile, Lochstoer and Muir (2020) find that due to agents' slow-moving beliefs about stock market volatility, their expectations initially underreact to news, followed by an overreaction. In another related literature on agents' perception of risk and its effects on the macroeconomy, López-Salido et al. (2017) find that elevated credit sentiment in the United States harms growth, whereas, stock market sentiment has no significant effect on growth. Pflueger et al. (2020) identify a positive relationship between risk perception and investment. In this paper, we propose a measure of risk perceptions that is built on a model of agents' beliefs of risk that can be estimated for various countries in a long time-series. The measure is closely related to other risk perception/appetite proxies, including Pflueger et. al (2020)'s PVS. We then provide evidence that risk perceptions in stock markets are an important driver of economic fluctuations and risk cycles are not only isolated to the issuance and pricing of credit, as concluded by López-Salido et al. (2017).

Second, in earlier literature, Levine and Zervos (1998), Beck et al. (2000), Beck and Levine (2002), and Levine (2006), among others, stress the pivotal role of the structure of the financial system for economic growth. More recent literature, including Durdu et al. (2020), Avdjiev et al. (2016), Rey (2018), and Jordà et al. (2018) focuses on the importance of the U.S. financial system driving global financial system, which in turn affects economic growth. We add a broad historical and international perspective on the effects of global financial risk cycles on business cycles.

Third, in this paper, we draw on the methodological contributions of our earlier work, Danielsson, Valenzuela, and Zer (2018), where we identify the importance of separating low risk from high risk in predicting the likelihood of crises. In this paper, we study the effects of risk perceptions—based on a Bayesian learning model of a low-risk environment—on growth rather than banking crises. Moreover, while Danielsson, Valenzuela, and Zer (2018) solely focus on the domestic risk environment, in this paper, our results underline the importance of the global risk environment. Finally, we show that different mechanisms are appropriate for predicting growth than banking crises.

We finally contribute to the vast literature on the effects of financial risk on growth (Bloom, 2009; Bloom et al., 2018). We add to this literature by showing an asymmetric impact of low and high risk on growth.

2 Data and empirical approach

2.1 Volatility, risk perception and the duration of low risk

Suppose the variance of financial returns (σ_t^2) follows a first-order autoregressive process with a time varying mean, similar to Hamilton (1989):

$$\sigma_t^2 = \gamma_0 + \gamma_1 \mathbb{1}_t + \beta\sigma_{t-1}^2 + \eta_t, \tag{1}$$

where $\gamma_0, \gamma_1 > 0$ to ensure positive variance. The indicator variable $\mathbb{1}_t$ indicates whether the volatility state is high or low:

$$\mathbb{1}_t = \begin{cases} 0 & \text{if } x_t = \text{Low} \\ 1 & \text{if } x_t = \text{High}. \end{cases} \tag{2}$$

x_t is an unobservable Markov switching binary state variable with symmetric transition probabilities $q > 0.5$:[4]

$$\Pr(x_{t+1} \mid x_t) = \begin{cases} q & \text{if } x_{t+1} = x_t \\ 1-q & \text{if } x_{t+1} \neq x_t. \end{cases} \tag{3}$$

Economic agents' investment decisions are based on whether volatility is high ($\mathbb{1}_t = 1$) or low ($\mathbb{1}_t = 0$). As agents neither observe the volatility nor the volatility state, $\mathbb{1}_t$, they base their decisions on the posterior probability of the value of $\mathbb{1}_t$. In order to calculate the posterior, they estimate the volatility ($\hat{\sigma}_t$) and use it to construct a signal (s_t) on the volatility state:

$$s_t = \begin{cases} \text{low} & \text{if } \hat{\sigma}_t \text{ is low} \\ \text{high} & \text{otherwise.} \end{cases} \tag{4}$$

The state contingent probability distribution of the signal is:

$$\Pr(s_t = \text{low} \mid x_t = \text{Low}) = \Pr(s_t = \text{high} \mid x_t = \text{High}) = p > 1/2. \tag{5}$$

[4]Since volatility clusters, a period of low volatility is more likely to follow a period of low volatility than high volatility. $q > 0.5$ ensures that the state is persistent.

The agent starts each year with a prior belief (α_t) about the current state, x_t, conditional on having observed a history of signals $\{s_1, s_2, ..., s_{t-1}\}$. Bayesian updating implies that the posterior belief of the volatility being in the low risk state is updated by:

$$\alpha_{t|t} = \frac{\Pr(s_t \mid x_t = \text{Low})\, \alpha_t}{\Pr(s_t \mid x_t = \text{Low})\, \alpha_t + \Pr(s_t \mid x_t = \text{High})(1 - \alpha_t)}. \tag{6}$$

The Markov transition probabilities imply that the prior belief in year $t + 1$ is given by:

$$\alpha_{t+1} = q\, \alpha_{t|t} + (1 - q)(1 - \alpha_{t|t}). \tag{7}$$

The agents' posterior beliefs of low risk ($\alpha_{t|t}$) drive their appetite for risk. However, as the probabilities p and q are not observable, we cannot directly construct the posterior. However, we can use (6) and (7) to construct a variable that proxies for the posterior, what we term the duration of low risk, DLR. Since $p, q > 0.5$, it follows from (6) and (7) that signals with the same value are more likely to follow each other than signals of the opposite value. Consequently, the posterior is persistent, where each subsequent identical low signal pushes the posterior towards one at a decreasing rate. We, therefore, propose a proxy for the posterior belief for low risk as:

$$\text{DLR}_t = \frac{1 - \theta}{\theta(1 - \theta^{N+1})} \sum_{j=0}^{N} \theta^{j+1} \left(1 - \hat{\mathbb{1}}_{t-j}\right) \tag{8}$$

where N is the number of years the volatility state has been consecutively estimated as low, the persistence parameter is $0.5 < \theta < 1$, and $\hat{\mathbb{1}}_t$ is the agent's estimate of the volatility state in (2). The first term normalizes DLR so that it is bounded above at one. It is then straightforward to show that:

$$\text{DLR}_t \quad = \quad \left[(1 - \theta)\left(1 - \hat{\mathbb{1}}_t\right) + \theta \text{DLR}_{t-1}\right]\left(1 - \hat{\mathbb{1}}_t\right) \tag{9}$$

The persistence parameter (θ) follows from the weight the agents attach to historical observations when constructing their posterior beliefs. As it is less than one, (9) implies that past observations are increasingly down-weighted. Hence, when the volatility state stays low, DLR increases but at a decreasing rate.

While it is not possible to use data to ascertain whether DLR adequately captures the posterior, we can use Monte Carlo simulations with reasonable parameters. We first simulate thousand signals across a range of values of p and q and then compute the posterior probability ($\alpha_{t|t}$) and DLR using the same simulated signals for a given θ. The correlation between DLR with $\alpha_{t|t}$ is between 0.70 and 0.93 when p, q, θ range from 0.70 to 0.95, and hence, we are confident that DLR is a high-quality proxy for the posterior. The larger the DLR is, the higher the agent's posterior probability of risk being low is. Therefore, DLR captures the agents' perception of risk and affects their risk appetite.

That leaves the question of what value of θ we should use when we estimate DLR. Equation (9) has a familiar functional form as the exponentially weighted moving average volatility model, not surprising as both models capture volatility clusters. The persistence parameter in such volatility models is generally found to be quite high, typically with $\theta \geq 0.90$. As a consequence, we opted to set $\theta = 0.90$ in our construction of DLR. In Section 4, we show that the results are robust to a wide range of θ values or when we do not consider any decaying factor and instead simply count the number of years that a country stays in a low volatility stage. DHR is constructed analogously.

2.2 Estimating risk cycles

We estimate DLR (and DHR) for each country separately, by first calculating the annual realized volatility as the standard deviation of monthly real market returns over a year.[5] To account for different inflation dynamics throughout the time and across countries, we adjust nominal returns with the consumer price index (CPI). In Section 4, we show that using nominal market returns or absolute value of returns to estimate annual volatility does not materially change our findings.

Alternatively, given that corporate bond spreads are informative about credit conditions and the real macroeconomic outcomes (Gilchrist et al., 2009), we could have used spread data to drive DLR. However, country-level historical cross-sectional data on bond spreads (including Treasury–corporate yield spreads and high yield–investment grade yield spreads) are scarce. Moreover, the agents' risk appetite should be reflected in the aggregate stock market prices, consistent with traditional rational asset pricing models (Bansal and Yaron, 2004; Pflueger et al., 2020).[6] Hence, we estimate DLR using stock prices, given that it is more readily available in a consistent form from any country with a stock market.

Second, after calculating the realized volatility estimates, $\hat{\sigma}_{i,t}$, we obtain the low

[5] Instead, we could have estimated a conditional volatility model from the GARCH family (see Engle, 1982; Bollerslev, 1986, 1987). We do not think such models are suitable for the annual volatility we require. Not only is the half-life of shocks to GARCH volatility typically less than one year, but such models also require hundreds of observations for estimation, a luxury we do not have. Similarly, we could have used Pakel et al. (2020) composite maximum likelihood, which requires a balanced panel and an assumption that the GARCH dynamic parameters are constant across countries, an assumption we are unwilling to make.

[6] In addition, Gebhardt et al. (2005); Hong et al. (2012) find that stock returns have predictive power for bond returns as bond prices adjust slower than stock prices to information about changing default risk. Along similar lines, Downing et al. (2009) show that the US corporate bond market is less informationally efficient than the stock market.

and high volatilities ($\hat{\sigma}^{\text{low}}_{i,t}$, $\hat{\sigma}^{\text{high}}_{i,t}$), analogous to receiving high and low signals in (4):

$$\begin{aligned}\hat{\sigma}^{\text{high}}_{i,t} &= \begin{cases} \hat{\sigma}_t - \hat{\tau}_{i,t} & \text{if} \qquad \hat{\sigma}_t > \hat{\tau}_{i,t} \\ 0 & \text{otherwise,} \end{cases} \\ \hat{\sigma}^{\text{low}}_{i,t} &= \begin{cases} \hat{\sigma}_t - \hat{\tau}_{i,t} & \text{if} \qquad \hat{\sigma}_t \leq \hat{\tau}_{i,t} \\ 0 & \text{otherwise,} \end{cases}\end{aligned} \tag{10}$$

where $\hat{\tau}_{i,t}$ is the estimated trend of volatility. In particular, a country is in its low volatility state, if the estimated volatility is below the trend. Because a particular measurement of volatility might be seen as worryingly high in one country/time and as comfortably low in another, it is necessary to find the appropriate trend for each country. We estimate trend via a one-sided Hodrick and Prescott (1997) (HP) filter.[7,8]

$$\begin{aligned}\hat{\tau}_{i,t}(\lambda) = \min_{\{\tau_{i,t}(\lambda)\}_{t=1}^{T_i}} & \sum_{t=1}^{T_i} \left[\sigma_{i,t} - \tau_{i,t}(\lambda)\right]^2 \\ & + \lambda \sum_{t=2}^{T_i-1} \left\{\left[\tau_{i,t+1}(\lambda) - \tau_{i,t}(\lambda)\right] - \left[\tau_{i,t}(\lambda) - \tau_{i,t-1}(\lambda)\right]\right\}^2, \\ & \qquad i = 1, \ldots, N,\end{aligned} \tag{11}$$

where T_i is the number of observations for country i, or a subperiod if the financial markets were interrupted, and the smoothing parameter λ quantifies the degree to which volatility deviates from its trend and thus the shape of the estimated cycle. The choice of the smoothing parameter λ depends on the underlying series. The literature suggests a value of 6.25 to 1600 for different frequencies of GDP (Ravn and Uhlig, 2002). However, a larger λ is needed for volatility, because of its clustering nature. Otherwise, a very small λ would make the estimated trend very volatile and it would follow very closely the volatility series itself. Following our earlier work (Daníelsson et al., 2018), we set $\lambda = 5000$. In Section 4, we apply

[7] As our analysis builds on predictive regressions, we use only past information when constructing the explanatory variables. Hence, we employ a one-sided HP filter. Moreover, in some countries, there are gaps in the data, either because economic historians haven't collected the data or markets have been otherwise interrupted. In those cases, we restart the calculation, with a new HP filter.

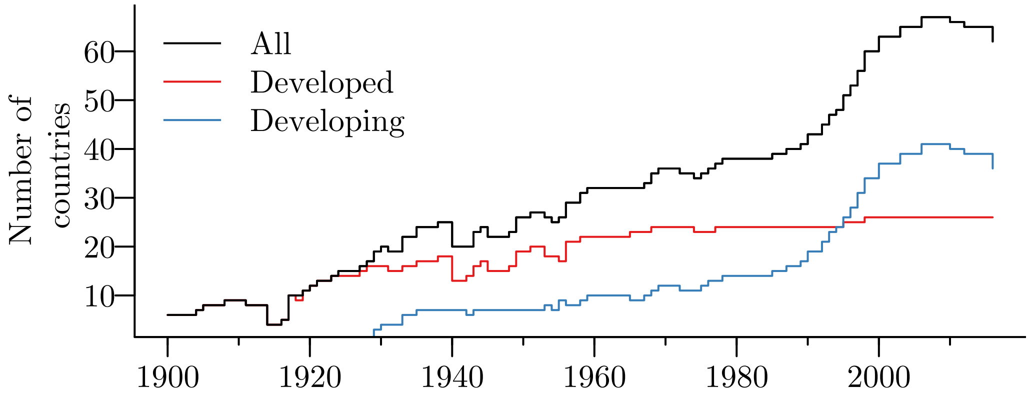
[8] The HP filter has come under criticism from Hamilton (2018). However, as argued by Drehmann and Yetman (2018), the choice of an indicator is driven by the application, and in their particular case—the credit gap as an early warning indicator for financial crises—the HP filter performs better. We reach a similar conclusion in our empirical analysis. Although similar, the volatility trend obtained from the HP filter is smoother over time than the Hamilton trend and hence, more suitable for our purposes. Accordingly, we use the HP filter in baseline specifications and provide the robustness of our findings by using the linear projection method proposed by Hamilton (2018) in Section 4.

various smoothing parameters, concluding that the results are indifferent to the chosen parameter.

We collect monthly stock market indexes from the Global Financial Data (GFD), with data available for 73 countries, from 1900 to 2016. On average, we have 55 years of observation per country. At the beginning of the sample, we have observations on only seven countries, the United States, Great Britain, Germany, France, Belgium, Australia, and Denmark and over time, as shown in Figure 1, the number of countries increases steadily (Table A1 in Appendix A lists individual countries' coverage). There are two sharp upticks in the number of countries with stock markets following World War I and the 1990s. The largest increase in the sample size comes from newly independent emerging countries establishing stock markets, identified as the blue line in Figure 1.

Figure 1: Data coverage

The number of countries with available stock market return data from 1900 to 2016. The classification into developed and developing is from the International Monetary Fund.



We show the volatility and the estimated trend for the United States in Figure 2 while presenting the remainder of the countries' volatilities and trend in the webappendix, available at `modelsandrisk.org/appendix/risk-cycles/`.

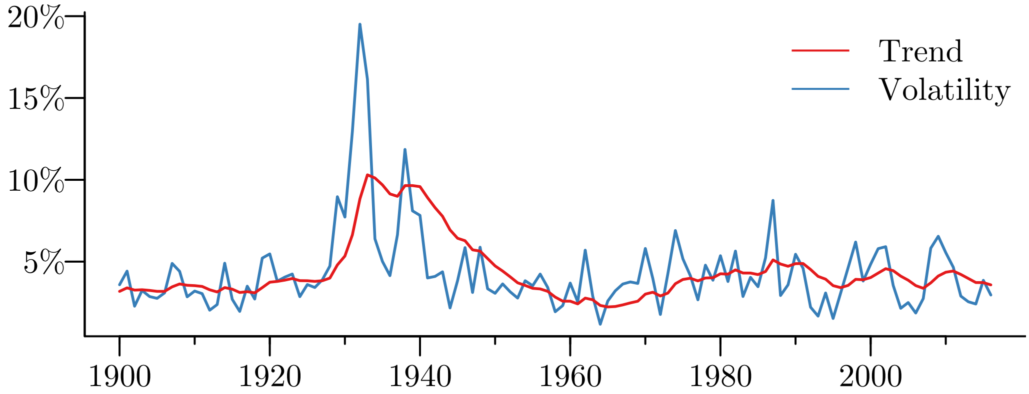
Finally, we use the estimated low and high volatilities to construct the signal $(\mathbb{1})$ and calculate DLR (and DHR). We present DLR and DHR estimates for each country in our sample in the webappendix, available at `modelsandrisk.org/appendix/risk-cycles/`.

2.3 The global risk cycle

The map of rises and falls in global DLR constitutes the global risk cycle, capturing the aggregate risk appetite of economic agents across the globe. The global DLR (G-DLR_t) is obtained as the GDP-weighted average of the local measure ($\text{DLR}_{i,t}$)

Figure 2: United States volatility and trend

Annual volatility and estimated trend for the United States. Volatility is calculated as the standard deviation of the previous 12 monthly real stock market returns. The trend is calculated by a one-sided Hodrick-Prescott filter with a smoothing parameter of $\lambda = 5000$.



across all countries with data in year t. G-DHR$_t$ is calculated similarly.[9] The G-DLR measure in Figure 3 highlights NBER recession dates and marks key events in world economic history. Visual inspection indicates that high G-DLR presages stress events—for example, in the late 1920s before the Great Depression, in the mid-1990s before the Asian crisis, and in the mid-2000s before the 2008 crisis.

Within the entire sample, one episode stands out as anomalous, World War II. Not only do the number of countries in the data set fell, but many of the countries with open stock markets in the sample were also occupied, and markets were disrupted in various ways, with arbitrary closures and confiscation, currency reforms, or very high inflation. We, therefore, drop the World War II years (1939–45) from the regressions.

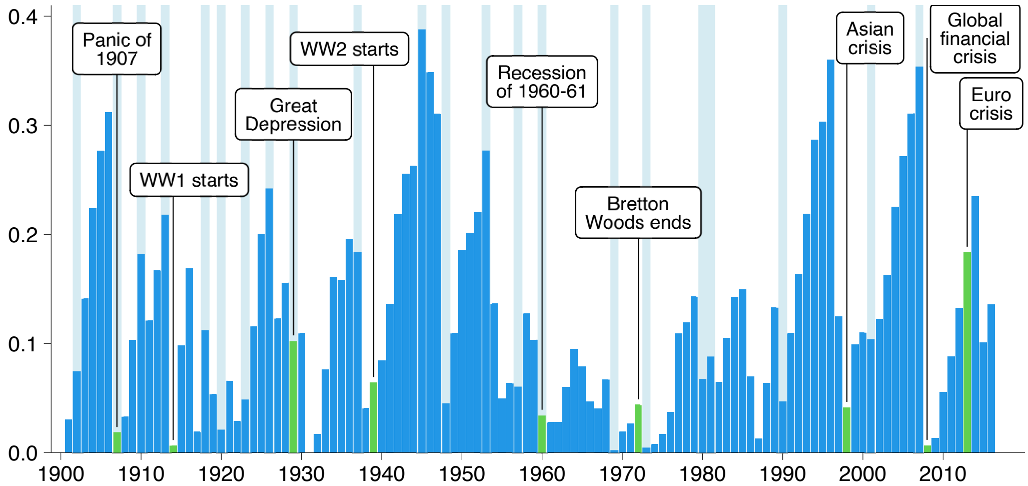
2.4 Assessing the validity of DLR as a risk perception measure

Our DLR measure captures agents' posterior probability of risk being low so that higher DLR measurements are associated with reduced risk perceptions, inducing the agents to seek more risk. We, therefore, expect DLR to be closely related to other proxies of risk perception and risk appetite, such as forward-looking volatility and various credit market indicators. Furthermore, because a lower perception of risk should induce agents to take on more risk, we expect them to be reflected

[9] As the number of countries varies over time, the global risk is constructed from an unbalanced panel. Hence, we check the robustness of our findings when global risk is obtained from a balanced panel considering current G7 constituents (United States, United Kingdom, France, Germany, Italy, Canada, and Japan). The results are presented in Section 4 and the main findings are robust.

Figure 3: Global duration of low risk

The global duration of low risk (G-DLR$_t$) is calculated as the gross domestic product-weighted average of the local measure (DLR$_{i,t}$). DLR$_{i,t}$ is defined in (9), considering the consecutive number of years in which stock market volatility remains low for country i in year t with decaying weights. NBER recession dates are highlighted and relevant economic events are marked in the figure.



in increased demand for risky assets. We use panel regressions to estimate the correlation of DLR with stock market returns. Finally, we explore why DLR could vary over time.

As the literature focuses on U.S. proxies of risk appetite, we pick the U.S. DLR and calculate the correlation between DLR and the various proxies: The CBOE Volatility Index (VIX), Bekaert et. al (2019)'s risk aversion measure (BEX), Pflueger et. al (2020)'s PVS, demand and credit standards of corporate loans from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS), and finally corporate bond spreads, measured as the difference between BAA and AAA yields.

Table 1 Panel A shows that the Pearson correlation coefficient between DLR and the measures we consider ranges from 0.36 to 0.75 (in absolute terms), all significant at a 5% level. Increases in DLR are associated with lower levels of the VIX and BEX risk aversion measures. Being one of the closest measures, at least conceptually, PVS is derived by using firm-level stock price volatility. We find that when PVS is relatively high, so does DLR. Measures of corporate credit conditions, in particular the fraction of banks that report strong demand for commercial and industrial loans and the tightening of credit standards for such loans (rows 4 and 5), are both significantly correlated with DLR. Finally, DLR significantly increases at the same "good" times when corporate spreads tighten (row 6).

We further expect DLR to be significantly correlated with contemporaneous stock returns, because agents' risk perceptions should be reflected in aggregate stock prices. A lower perception of risk should induce agents to take on more risk, causing prices to rise. We investigate that assertion in a panel setting by regressing real stock index returns on DLR, controlling for the standard determinants of stock returns; including dividend yields, realized stock market volatility, changes in short-term interest rates, term premium, and macroeconomic variables (inflation, the degree of institutionalization, and the level of GDP), along with year and country fixed effects. Data are from the Global Financial Data, Maddison (2003), Polity IV, and Baron and Xiong (2017). We report the results in Panel B of Table 1. We find that DLR is significantly related to contemporaneous stock market returns at a 5% level. A one standard deviation increase in DLR is associated with an increase of 1.3% in annual real returns.

Ultimately we find that DLR is highly correlated with extent proxies of risk perception and strongly correlated with stock returns when controlling for the standard determinants of stock returns, lending further support to our assertion that DLR is a good proxy for risk perception.

Then a question remains: why do risk perceptions vary? What could be the possible shocks driving DLR over time? Considerable evidence suggests that financial risk varies with 1) the arrival of news (Bomfim, 2003; Pflueger et al., 2020); 2) macroeconomic or policy uncertainty (Pastor and Veronesi, 2012); 3) market liquidity (Valenzuela et al., 2015); and 4) monetary policy shocks (Rey, 2018). To identify such connections, we regress U.S. DLR on the contemporaneous positive macroeconomic news surprises of Scotti (2016), Bekaert's et al. (2019) uncertainty index, liquidity shocks as in Bali et al. (2014), and Romer and Romer's (2004) monetary policy shocks.[10]

We show the univariate regression results in Table 2, where the sample size is determined by the availability of the particular measure. Positive macroeconomic news is associated with falling risk perceptions (higher DLR) as the expectations of consumers and investors adjust following good news arrivals (Forni et al., 2017; Barsky and Sims, 2011). Moreover, DLR is positively associated with low macroeconomic uncertainty, excess financial market liquidity, and looser than expected monetary policy decisions.

[10]The Scotti (2016) surprise index aggregates macroeconomic U.S. news releases (such as GDP, industrial production, retail sales) and considers the deviation of the release from the Bloomberg consensus forecasts. A positive value suggests "good news": economic releases on balance are higher than consensus. Bekaert et al. (2019) uncertainty index approximates macroeconomic uncertainty and is based on the conditional variance of U.S. industrial production growth. Liquidity shocks are defined as the difference between the stock market turnover and its past 12-month average, per Bali et al. (2014). Finally, Romer and Romer (2004) identify changes in the federal funds rate targets surrounding Federal Open Market Committee meetings based on the Federal Reserve Greenbook forecasts. A positive monetary policy surprise value indicates looser-than-expected monetary policy decisions.

3 Empirical methodology and results

3.1 Econometric set-up

Our main empirical device is impulse responses obtained from Jordá's (2005) local projection method. Specifically, we use a panel setting to regress the dependent variable $t+h$ years in the future, on a variable that is shocked as well as other independent variables observed at t or earlier. We indicate country by i and year by t:

$$\begin{aligned} \Delta y_{i,t+h} = & \quad \beta^h S_{i,t} + \textstyle\sum_{k=1}^{L} \delta_k^h \Delta y_{i,t-k} + \sum_{k=1}^{L} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}, \\ h = & \quad 0, \ldots, 5, \\ S_{i,t} = & \quad \mathrm{DLR}_{i,t} \vee \text{G-DLR}_t \vee \mathrm{DHR}_{i,t} \vee \text{G-DHR}_t, \end{aligned} \tag{12}$$

where $\Delta y_{i,t+h} = y_{i,t+h} - y_{i,t+h-1}$ with $y_{i,t}$ is the log-GDP of each country in the sample. We obtain annual GDP per capita from the from the Maddison (2003) database, available at `http://www.ggdc.net/maddison/`, used by several authors, including Acemoglu et al. (2008) and Reinhart and Rogoff (2009). The shock variable is $S_{i,t}$ and the impulse response is hence β^h. α_i^h are country fixed effects, and η_t^h are decade fixed effects.[11] We set the number of lags at five ($L = 5$).

$X_{i,t}$ is the vector of control variables. Besides controlling for lagged growth, as well as DLR and DHR and their global counterparts, we use other control variables identified in the literature affecting economic growth. Following Daníelsson et al. (2018), we include the inflation rate and the institutional characteristics of a country as control variables. Inflation is calculated as the annual percentage change in the CPI, obtained from GFD. POLCOMP is the proxy for the institutional characteristics of a country and from the Polity IV Project database. We additionally include changes in short-term interest rates and log per-capita income. Interest rates affect GDP, investment, and inflation (see e.g., Taylor, 1993). We collect three-month Treasury bill yields from the GFD. Finally, we include per-capita income as a proxy for an aggregate financial development indicator, as the structure of the financial system plays a pivotal role for economic growth (Levine and Zervos, 1998; Levine, 2006; Beck and Levine, 2002). While many financial development indicators have been proposed in the literature, such as stock market capitalization and banking-sector depth measures, we include per capita income as a proxy for an aggregate financial development indicator, mainly due to historical

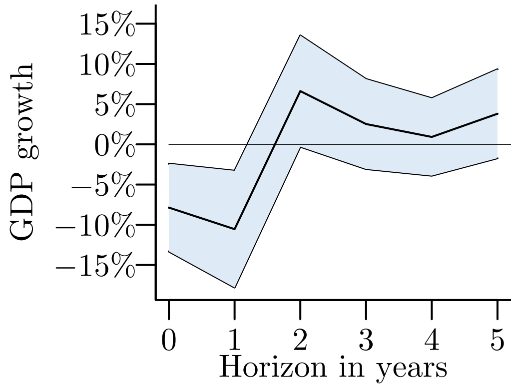
[11] We include 10-year fixed effects to control for financial and economic development throughout time. Year fixed effects are not considered, as we have global risk appetite as an explanatory variable, which does not change country by country. Including such a variable in a panel setting is akin to including a time-series trend. In section 4, we include 5-year and 20-year fixed effects as robustness.

data limitations (see, for e.g., Levine, 2006, for a survey). Appendix B lists all variables used in the analysis, along with their definitions and data sources.

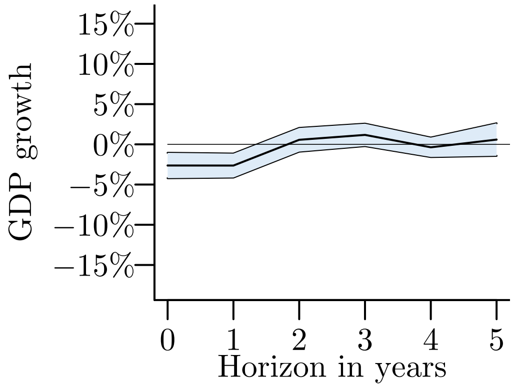
3.2 Risk cycles and growth

Figure 4: The impact of risk cycles on growth

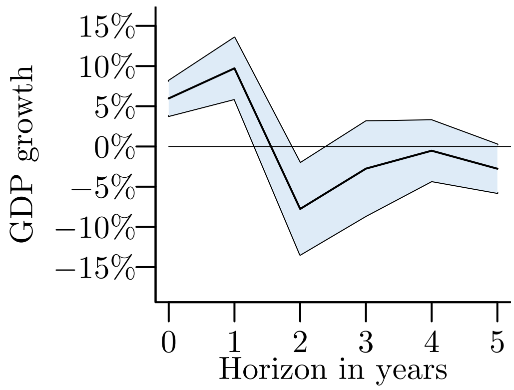
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to the duration of high risk (DHR) and duration of low risk (DLR). In Panel (a), we present the results for a shock in global DHR. Panel (b) shows the results for local DHR. In Panel (c), we present the results for a shock in global DLR (G-DLR). Finally, in Panel (d), we show the results for the local low-risk phase. Global and local measures are introduced in Section 2. In all cases, we run regressions (12) with log-GDP growth as the dependent variable. All regressions include the lagged values of the inflation rate, the degree of political competition, log-GDP, change in short term interest rates, the dependent variable, duration of low risk (DLR), duration of high risk (DHR), their global counterparts (G-DLR and G-DHR), and country and decade fixed effects. We dually clustered standard errors at the country and year levels.



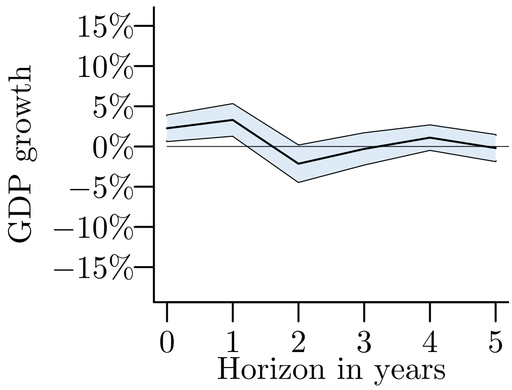
(a) A shock to G-DHR



(b) A shock to DHR



(c) A shock to G-DLR



(d) A shock to DLR

We start by investigating the effects of global and local risk cycles on business cycles. Although the stock market data are available for 73 countries, the sample coverage of other series is more sparse. Considering the missing observations, the sample used to run (12) contains 55 countries, spanning from 1900 to 2016. Figure 4 shows the impact of global and local risk cycles on growth. Panels (a) and (b) reveal that a positive shock to local DHR — that is, lengthening of a high volatility state—has an unambiguous negative impact on economic growth, contemporaneously and in the next year. The effect of global DHR (G-DHR) on growth is stronger than local. A one-standard-deviation increase in local DHR decreases economic growth 0.8% over $h = 0$ and $h = 1$, whereas the economic impact of G-DHR is about double of its local counterpart, with a cumulative contraction of 1.4%.

The short-term negative impact of DHR on growth is consistent with the extant literature. Increased DHR predicts a slowdown of economic activity in the short term, as it is expected to increase uncertainty, hence, delaying investment, or to exacerbate information asymmetry problems, limiting credit available to firms (Dixit and Pindyck, 1994; Bloom et al., 2018; Gilchrist et al., 2014; Ferreira, 2016).

We then examine the effects of DLR on growth in Panels (c) and (d). If its impact were symmetric to DHR, we would observe a short boom effect on the growth cycle, but that does not happen. The impact of the low-risk phase is much different from that of the high-risk phase: both larger in magnitude and longer-lasting — a boom-to-bust growth cycle compared with a bust only. The impact of DLR on growth is positive contemporaneously and the following year, turning negative two years afterward. As the low-risk environment lasts longer, so does the risk appetite of economic agents, initially leading to higher growth, but ultimately resulting in a reversal amid accumulated financial vulnerabilities.

A one standard deviation increase in G-DLR leads to a 1.5% increase in GDP growth of a typical country over the first two years, followed by a reduction of 0.7% in GDP growth. Overall, over the boom-to-bust cycle cumulatively, a one-standard-deviation increase in G-DLR increases GDP growth by about 0.8%. Furthermore, G-DLR has a stronger economic impact than does its local counterpart in its contribution to local growth: The amplitude of its boom-to-bust growth cycle is significantly higher and its cumulative impact is about double that of DLR.[12]

Overall, our results raise questions about the specific mechanisms that lead to the boom-to-bust growth cycle, underscoring the importance of the global low-risk environment. For the rest of the empirical analysis, we address those questions, focusing on global low risk.

[12]Our findings on the importance of G-DLR on local economic cycles are in line with Cesa-Bianchi et al. (2020), who identify the global financial factor as the common shock driving country-specific realized volatilities. They show that the global factor explains a significantly higher variation of the country-specific output growth, compared to the proportion explained by the country-specific volatility shocks.

3.3 Global low risk and growth: endogeneity concerns

When running the regression in (12), we assume that shocks to G-DLR are exogenous to growth, contemporaneously, and in the future. Such an assumption might be violated if some other large shock, such as a monetary policy shock, affects both realized volatility (and hence, G-DLR by definition) and the current state of the economy (through the changes in expected future volatility). In other words, the time-dependent nature of volatility might imply that current shocks are propagated into the future, causing identification issues. We use a two-pronged approach to alleviate the endogeneity concerns: 1) a two-stage regression specification similar to López-Salido et al. (2017); 2) The news shock approach of Berger et al. (2020).

In the first stage of the two-stage regression specification, we regress G-DLR on past values of a set of plausibly exogenous control variables, Z_t, that can affect agents' perceptions of global risk. In particular, we include natural disasters, terrorist attacks, political shocks, liquidity shocks, and realized volatility. Natural disasters, terrorist attacks, and political shocks are from Baker et al. (2020) for 60 countries since 1970. We calculate the GDP-weighted cross-sectional averages to obtain the corresponding global shock.[13] Liquidity shocks are defined as the difference between the U.S. stock market turnover and its past 12-month average, per Bali et al. (2014). In addition, we control for the stock market realized volatility as it affects G-DLR by definition. We consequently run the following regression:

$$\text{G-DLR}_t = \theta + \sum_{k=1}^{5} \gamma_k Z_{t-k} + \epsilon_t, \tag{13}$$

We calculate the fitted estimate of G-DLR $\left(\widehat{\text{G-DLR}}\right)$, which we interpret as the predictable component of G-DLR, driven by past market risk perception as opposed to changes in expectations of future volatility. For completeness, we also estimate the fitted estimate of G-DHR using (13). We then regress the GDP growth rate on $\widehat{\text{G-DLR}}$ controlled for the lagged values of $\widehat{\text{G-DLR}}, \widehat{\text{G-DHR}}$, along with the other variables used in our baseline specification (12). That is:

$$\Delta y_{i,t+h} \quad = \quad \beta^h \widehat{\text{G-DLR}}_t + \sum_{k=1}^{5} \delta_k^h \Delta y_{i,t-k} + \sum_{k=1}^{5} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}. \tag{14}$$

Thus, even though this approach mechanically resembles an instrumental variables

[13]Natural disasters include extreme weather events such as droughts, earthquakes, and floods obtained from the Center for Research on the Epidemiology of Disasters (CRED). Terrorist attacks data include all terrorist bombings which result in more than 15 deaths from the Center for Systemic Peace (CSP). Political shocks include coups and revolutions obtained from the CSP.

(IV) approach, Z_t does not necessarily satisfy the exclusion restrictions that are required in IV estimation. Thus, we still do not make strong identification claims.

We report the results in Table 3 panel A. As we use an estimated regressor ($\widehat{\text{G-DLR}}$) in the second stage, we bootstrap the standard errors with 1,000 sample draws clustering at the country and year level. The first-stage results show a significant relationship between the control set and G-DLR with an adjusted R^2 of 66%. The second-stage results confirm our main finding: $\widehat{\text{G-DLR}}$ has strong explanatory power for future growth. Indeed, under the two-stage approach, the impact of G-DLR on growth lasts longer and, in particular, continues to be significant in year three.

Second, we follow the methodology proposed by Berger et al. (2020). Since realized volatility is autocorrelated (the so-called GARCH effect), current realized volatility affects future expected volatility (i.e., uncertainty about the future), which in turn is related to current economic conditions. Berger et al. (2020) suggest a methodology for addressing such identification problem, whereby we construct news shocks driven by implied volatility and orthogonal to current realized volatility innovations. We then incorporate those shocks into our baseline on model (12) and examine the effects of G-DLR shocks on growth in the presence of simultaneous news and realized volatility shocks in the economy.

As this identification approach depends on options markets data, for which long time horizons are only available in the United States, we focus on the U.S. from 1984 to estimate the news shocks. Accordingly, we first estimate a Vector-Auto-Regression (VAR) model with the following moving average representation:

$$Y_t = (I - F(1))^{-1}C + B(L)A\varepsilon_t, \tag{15}$$

where

$$B(L) = \sum_{j=0}^{\infty} B_j L^j = (I - F(L))^{-1}. \tag{16}$$

Y_t includes stock market realized volatility, annualized one month implied volatility, changes in three-months Treasury Bill rates, CPI inflation, and GDP growth rate, i.e., $[RV_t, IV_t, \Delta STIR_t, INF_t, \Delta \log GDP_t]$. C denotes a vector of constants. $F(L)$ is a matrix of coefficients in the structural VAR setting, with the lag operator L. Realized volatility shocks are ordered first and news shocks are ordered second in the structural VAR setting. The identifying assumption is that news shocks do not affect realized volatility contemporaneously, but realized volatility can cause changes in expected future volatility.

We obtain changes in cumulative expected volatility up to time $t + n$ by:

$$E_t \sum_{j=1}^{n} RV_{t+j} - E_{t-1} \sum_{j=1}^{n} RV_{t+j} = \left(e_1 \sum_{j=1}^{n} B_j \right) A\varepsilon_t, \tag{17}$$

where $e_1 = [1, 0, \cdots]$ and n denote the horizon of the news shock. The RV shock is $e_1 A \varepsilon_t$ and the news shock is obtained by orthogonalizing (17) with respect to the innovation to RV by following Barsky et al. (2015) and Barsky and Sims (2011).

We report the estimated coefficients for G-DLR in Table 3 panel B, when we alter the baseline specification (12) by including the news or realized volatility shock along with a G-DLR shock. As we use estimated regressors (news and realized volatility shocks), we bootstrap the standard errors with 1,000 sample draws clustering at the country and year level. We find that the G-DLR shocks affect growth even under the presence of news and/or realized volatility shocks. Overall, these analyses increase our confidence in the effects of G-DLR on economic growth, although we remain cautious on the identification.

3.4 Risk perceptions, credit growth, and non-linearities

We have so far found that the aggregate effects of strengthening perceptions of low risk on growth are positive over the boom-to-bust cycle. In this section, we study two possible cases, where the impact of low risk on growth might be negative overall: when a country experiences a credit boom and when the low risk has persisted for a particularly long time. If a country is experiencing a credit boom, then its financial system is expected to be more fragile and less resilient to adverse shocks (see for example Schularick and Taylor, 2012; Aikman et al., 2017). Similarly, longer-lasting low-risk periods, compared with short-lived ones, could lead to a buildup of financial vulnerabilities, as financial vulnerabilities are procyclical and accumulate throughout economic expansions (Adrian and Liang, 2018). In either of the cases, even a small revision of beliefs can create a self-reinforcing feedback loop that impairs credit provision, lowers asset prices, and depress economic activity by amplifying the reversal in growth.

To examine these conjectures, we first use excess private non-financial credit as a proxy of financial system vulnerability as in Adrian et al. (2015); Basel Committee on Bank Supervision (2010). We define an indicator variable $I^q_{i,t}$ for whether a particular country is above or below a quantile (q) of credit growth in a given year, compared with other countries.

$$I^q_{i,t} := \begin{cases} 1 & \text{if credit growth}_{i,t} \geq \text{credit growth}^q_t \\ 0 & \text{otherwise,} \end{cases} \tag{18}$$

where credit growth^q_t is the q^{th}_t quantile in year t. We measure credit growth as the log first difference of credit to nonfinancial institutions, with data obtained from the Bank for International Settlements, available from 1953 for 40 countries. We then modify the impulse panel regressions in (12) to allow for two states, when credit is above or below the quantile q:

$$\begin{aligned}\Delta y_{i,t+h} = & \quad I^q_{i,t}\left(\beta^{h,\text{high}} S_t + \Gamma^{h,\text{high}} X_{i,t}\right) \\ & +(1 - I^q_{i,t})\left(\beta^{h,\text{low}} S_t + \Gamma^{h,\text{low}} X_{i,t}\right) + \alpha^h_i + \eta^h_t + \varepsilon_{i,t+h}, \\ h = & \quad 0, \ldots, 5, \\ S_t = & \quad \text{G-DLR}_t.\end{aligned} \tag{19}$$

$\beta^{h,\text{low}}$ and $\beta^{h,\text{high}}$ are the impulse responses of growth to a shock of G-DLR conditioning on credit growth below and above the quantile threshold (credit growth^q_t), respectively. In what follows, we refer to results from $\beta^{h,\text{low}}$ and $\beta^{h,\text{high}}$ as low and high, respectively.

Figure 5: The impact of global low risk on growth, conditional on the state of the credit cycle.

This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to the global duration of low risk (G-DLR) conditioning on excessive credit growth. G-DLR is introduced in Section 2. High credit growth is from (18) using the log difference of credit to nonfinancial institutions, with data obtained from the Bank for International Settlements, available from 1953 to 2016 for 40 countries. We run regression (19) and plot $\beta^{h,\text{high}}$ based on different quantiles to define excessive credit growth (0.5 and 0.9). For comparison, unconditional impulse responses for the period where we have available credit data are also plotted. All regressions include the lagged values of the inflation rate, the degree of political competition, log-GDP, change in short term interest rates, the dependent variable, duration of low risk (DLR), duration of high risk (DHR), their global counterparts (G-DLR and G-DHR), and country and decade fixed effects. We dually clustered standard errors at the country and year levels.

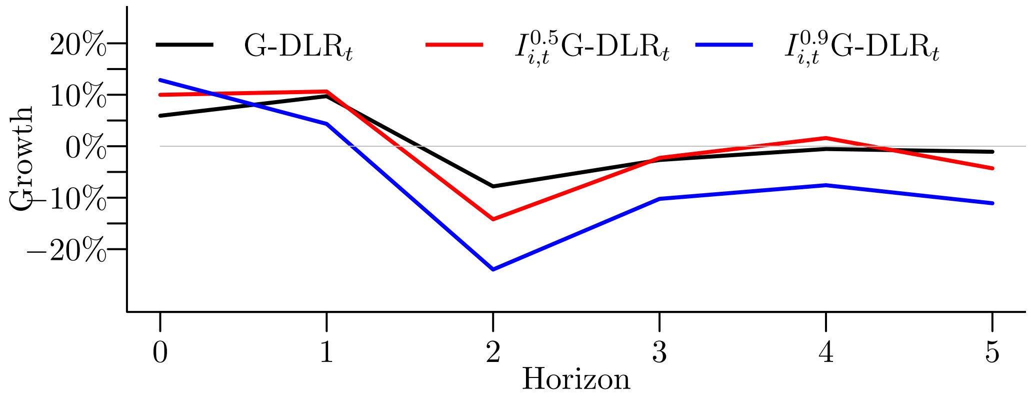


Figure 5 shows the estimated impulse responses for high credit states for different horizons based on quantiles 0.50 and 0.90. The results highlight an almost monotonic relationship between the amount of excessive credit and the impact of G-DLR on growth: the higher the excessive credit, the stronger the reversal in the second year. In particular, if a country is in the highest decile of credit growth in a certain year, the amplitude of the bust is triple what it would otherwise be, and is longer-lasting, making the overall impact negative. A one-standard-deviation increase in G-DLR decreases economic growth by 0.65% across the three-year cycle.

Second, we extend the baseline specifications (12) so that GDP growth is modeled as a third-degree polynomial in G-DLR:

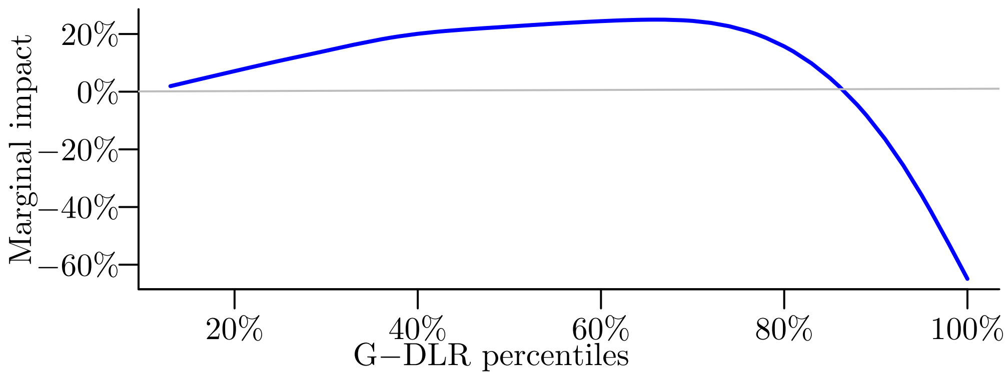
$$\begin{aligned} \Delta_h y_{i,t+h} &= \beta_1^h \text{G-DLR}_{i,t} + \beta_2^h \text{G-DLR}_{i,t}^2 + \beta_3^h \text{G-DLR}_{i,t}^3 \\ &+ \sum_{k=1}^{L} \delta_k^h \Delta_h y_{i,t-k} + \sum_{k=1}^{L} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}, \end{aligned} \tag{20}$$

where $\Delta_h y_{i,t+h} = y_{i,t+h} - y_{i,t-1}$ is the h-year *cumulative* GDP growth rate. After estimating (20), we calculate the marginal rate of return of cumulative GDP growth to G-DLR as:

$$\rho(\widehat{\text{G-DLR}}) = \frac{\partial \Delta_h y}{\partial \text{G-DLR}} = \widehat{\beta_1^h} + 2\widehat{\beta_2^h}\text{G-DLR} + 3\widehat{\beta_3^h}\text{G-DLR}^2. \tag{21}$$

In Figure 6 we plot $\widehat{\rho}$ at different quantiles of G-DLR over the boom-to-bust cycle—that is, two-year cumulative GDP growth. We find that for G-DLR smaller than its 85% quantile, the marginal impact of increasing G-DLR remains positive, but at a decreasing rate. Beyond the 85% quantile, the marginal impact of G-DLR on growth turns negative: a very-long low-risk environment today leads to a significant decrease in cumulative growth over the boom-to-bust cycle. In other words, the response of growth to increase in DLR is concave.

Figure 6: The non-linear impact of G-DLR on growth
This figure shows the estimated marginal rate of return of cumulative GDP growth to G-DLR ($\widehat{\rho}$), introduced in (21). We plot $\widehat{\rho}$ at different quantiles of G-DLR. To estimate $\widehat{\rho}$, we run regression (20) so that cumulative GDP growth is modeled as a 3rd degree polynomial in G-DLR.



Taken together, these results provide support for our notion of financial vulnerability-driven economic contraction. The bust cycle (reversal on growth) is especially strong in times of high credit growth and when low-for-long volatility environment persists. For instance, the 2008 global financial crisis was preceded by a long DLR period (in the United States, volatility stayed low for five consecutive years).

Moreover, the episode was a clear example of increased vulnerabilities in the financial system: both corporate, but especially household lending was excessive. In this case, our analysis shows that the aggregate effect of G-DLR on growth was negative.

3.5 Why does low risk cause a boom-to-bust cycle: Possible mechanisms

Why does perceived low risk affect economic growth? We surmise the reason lies in the particular interplay between risk-taking and growth through three primary channels: domestic investment, capital flows, and debt issuer quality. When investors perceive risk as low globally—G-DLR increases—they are more inclined to reach for yield. Free capital flows and the presence of a globalized banking system allows global investors to tilt their asset allocations towards riskier asset classes and countries (Bruno and Shin, 2015; IMF, 2019). The result is an immediate increase in capital flows, funded by global investors. Moreover, in such periods, increased risk-taking implies that even poor quality borrowers are more likely to be financed as in Greenwood and Hanson (2013), again boosting the growth at the expense of lower issuer quality. Eventually, however, high-quality investment opportunities are increasingly exhausted, leading to a reversal in investment and capital flows.

We use three data sources to examine three channels. First, we proxy private investment by gross capital formation (investment in fixed assets and inventories) as a percentage of GDP with data from the World Development Indicators (WDI) for 73 countries from 1960 to 2012. Second, we obtain total portfolio inflows data for each country (as a percentage of GDP) from the IMF, where the sample covers 55 countries from 1970 to 2012. Finally, we use the high-yield issuance share index constructed by Kirti (2020). Accordingly, when lenders are willing to allocate a larger share of credit to less-creditworthy borrowers, the high-yield share index increases. The data includes 38 countries with coverage going back to the early 1980s, primarily for advanced countries.

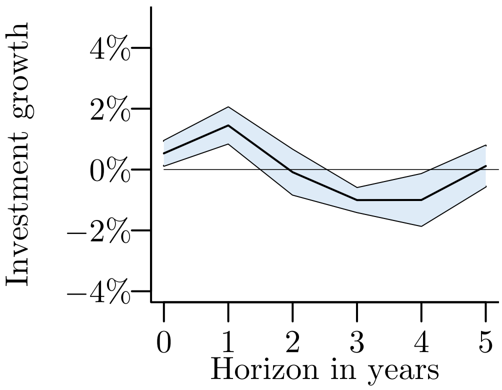
We run the baseline specifications (12) by replacing the endogenous variable with the growth of investment, capital flows, and high-yield share index, while keeping the same controls.[14]

Figure 7 shows that G-DLR has a strong impact on investment, capital flows, and

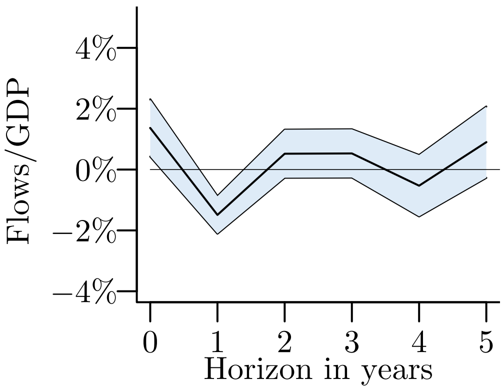
[14] Because U.S. monetary policy decisions may also affect the relative return on investment in foreign economies, it may affect capital flows across countries. However, by including U.S. monetary policy surprises instead of a change in interest rates, our sample size is reduced significantly. Hence, we leave the analysis with the surprise series estimated by Romer and Romer (2004) as a sensitivity analysis, reaching similar conclusions.

Figure 7: Impact of global low risk on investment, capital flows, and lending standards.

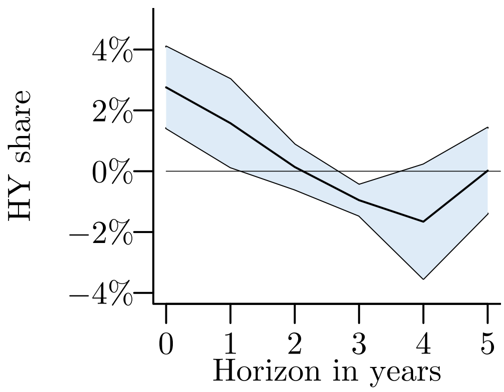
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of investment growth, changes in portfolio inflows, and debt-issuer quality to a shock to the global duration of low risk –G-DLR, introduced in Section 2. Private investment is proxied by gross capital formation (investment in fixed assets and inventories), as a percentage of gross domestic product (GDP), and we obtain the data from World Development Indicators for 73 countries from 1960 to 2012. Total capital inflows data (as a percentage of GDP) are obtained from the International Monetary Fund for 55 countries from 1970 to 2012. Lending standards are proxied via the high-yield bond issuance data constructed by Kirti (2020), spanning 38 countries from 1980 to 2016. We run regressions (12) by replacing growth with changes in portfolio inflows, growth of investment, and the log- high-yield (HY) share index as dependent variables. All regressions include the lagged values of the inflation rate, the degree of political competition, log-GDP, change in short term interest rates, the dependent variable, duration of low risk (DLR), duration of high risk (DHR), their global counterparts (G-DLR and G-DHR), and country and decade fixed effects. We dually clustered standard errors at the country and year levels. All variables are standardized to ease the interpretation.



(a) Shock to G-DLR



(b) Shock to G-DLR



(c) Shock to G-DLR

debt issuer quality. G-DLR has a positive short-run impact, with a reversal in the medium to longer-term. Specifically, as the world's low-risk environment increases by one standard deviation, a typical country's investment growth, changes in portfolio-flows-over-GDP ratio, and high-yield share will have an immediate increase of 0.53%, 1.37%, and 2.76% but followed by a reversal of -2.00%, -1.49% and -0.95%, respectively. We then study the impact of local DLR on investment, capital flows, and share of high-yield issuance. The results presented in Figure C1 in Appendix C indicate that local DLR has negligible effects on investment growth, portfolio flows, and debt-issuer quality.

Furthermore, we employ the two-stage regression and news shock approaches introduced in 3.3 to alleviate possible endogeneity concerns. For the former, we use the same $\widehat{\text{G-DLR}}$ estimated from (13). For the latter, we use the news shocks of Berger et al. (2020) estimated via (15) and (17). Table 4 shows that there is a boom-to-bust cycle in investment and capital flows following a shock in G-DLR. However, the evidence on the effects of G-DLR on HY-share issuance is mixed: a shock in G-DLR increases the high-yield issuance but a reversal does not necessarily follow.

4 Robustness

We execute 23 robustness tests, which can be classified under seven groups. First, we check whether the results are sensitive to the way we estimate the volatility trend, which is used to calculate low volatility. To this end, we estimate the volatility trend by applying the methodology proposed by Hamilton (2018). The estimated trend from the Hamilton filter is noisier than the estimates of the HP filter trend. To smooth them out, instead of keeping the last estimate for the trend at t, we calculate the average of the previous 20-years' estimates. We then keep the HP filtering, but estimate the volatility trend under various smoothing parameters ($\lambda = 1000$, $\lambda = 10000$, in addition to $\lambda = 5000$). We further examine different ways of measuring trend that is not based on filtering techniques: using historical mean and one-standard-deviation band. Accordingly, we mark a country as in a low volatility state if the current volatility is below the one-standard-deviation band.

Second, we conduct robustness tests on the definitions of volatility. Instead of estimating annual volatility as the standard deviation of 12 real monthly returns, we calculate volatility as the sum of absolute monthly real returns. Moreover, instead of using real stock market returns, we use nominal returns to estimate volatility.

In the third set of robustness tests, we examine whether our findings are sensitive to the definition of DLR. We examine different values for decaying factor θ ranging from 0.75 to 0.95 in equation (9), but for the sake of brevity we only report our results for $\theta = 0.85$ and $\theta = 0.95$. In addition, we check our findings when we do not apply any decaying factor and instead we count the number of consecutive years in which a country experiences a low volatility regime. Then, we consider the intensity of the deviations of volatility from its trend and calculate DLR as the sum of the volatility deviations when a country stays in a low volatility regime consequently.

Fourth, we examine whether the unbalanced nature of data affects our findings. G-DLR is calculated as the weighted cross-sectional average of local DLRs available in a given year in a highly unbalanced panel. We instead repeat the analysis using the current G7 countries (United States, United Kingdom, France, Germany, Italy, Canada, and Japan) and start the sample period in the year we have available stock market information for all of those countries, which is 1921, and recalculate G-DLR. Finally, we define G-DLR by using U.S. DLR only, while omitting the rest of the countries in the sample.

The fifth set of robustness tests includes additional control variables in our baseline specifications: credit spreads, change in exchange rates, U.S. monetary policy shocks, economic policy uncertainty (EPU) of Baker et al. (2016), and geopolitical risk index (GPR) of Caldara and Iacoviello (2018). Krishnamurthy and Muir (2017) find that the changes in output can be explained by unusually high credit growth coupled with unusually narrow bond credit spreads and thus credit spreads are useful predictors of economic activity. Therefore, we include U.S. bond spread data measured as the difference between BAA and AAA yields as a control variable. Avdjiev et al. (2016) argue that the U.S. dollar has replaced the VIX as the variable most associated with an appetite for leverage; that when the dollar is strong, risk appetite is weak. Therefore, we include the change in local exchange rates with respect to the U.S. dollar obtained from the GFD. We as well control for the U.S., monetary policy surprise series estimated by Romer and Romer (2004), covering 1970 to 2008. We include EPU and GPR indexes as we expect them to affect global risk-taking. Note that these variables are left as a robustness analysis because including them in the analysis reduces the sample size significantly.

Sixth, we execute sensitivity analyses on the econometric specification we employ by including 5-year and 20-year fixed effects instead of decade fixed effects in the main specifications. Then, instead of calculating double-clustered standard errors, we calculate them using Driscoll-Kraay standard errors as they are widely used in a long panel with a smaller number of cross-sectional observations.

Finally, we test the robustness of our findings during different subsamples. Our sample contains many distinct sub-periods, market structures, developments, and types of countries. The structure of financial markets was quite different for the early period, and stock markets became a much more central vehicle for financing economic activity, especially after World War II, with the general public investing in equities on a large scale. Moreover, emerging market economies started to develop stock markets. During the post-Bretton Woods era (after 1972), globalization increased, capital flows have become unrestricted, financial markets increasingly deregulated, trading computerized, and, most recently, global financial intermediation is taking place via the fixed-income markets rather than through banks. The number of developing countries is much larger in the past half a century than before, and the importance of capital flows is increasing. Moreover, we split our sample between developed and emerging countries classified by the IMF for the post-Bretton Woods era as it is when we have many emerging countries in the sample as seen in Figure 1.

The results are reported in Table 5. To ease the interpretation of the results, instead of plotting impulse responses for all of the specifications, we present the estimated coefficients from (12) for both local and global DLR. Overall, we find that the main results are qualitatively unaltered under the various robustness checks.

Row 25 presents the results when U.S. DLR is used as a proxy for global risk. Several authors have highlighted the pivotal importance of the United States for global financial cycles (Rey, 2018; Jordà et al., 2018; Avdjiev et al., 2016). With its reserve currency, the world's largest economy, and financial markets, financial risk in the United States could be particularly important for global risk, driving international risk-taking and, thus, affecting growth throughout the world. Indeed, US-DLR is able to explain about 30% of the variation in G-DLR. In comparison to the overall results with G-DLR, we find that US-DLR can explain a significant part in the changes in local growth. Thus, we conclude that the United States plays a pivotal role in the global financial cycles.

In Rows 41 through 48, we show that during the postwar and post-Bretton Woods eras, both local and global risk cycle matters in explaining economic growth, while the impact of global risk is significantly higher. The results are qualitatively similar over the whole sample period, supporting our findings. Finally, we find that the impact of G-DLR over three years is stronger for emerging countries than developed countries, with higher amplitudes of the boom-to-bust cycle. This finding highlights the pivotal role of global capital markets intermediating funds to such countries. In the end, limits to domestic bank lending in emerging countries may make them more dependent on international capital markets than developed countries. The risk appetite both for international investors who provide capital and for domestic investors who undertake capital projects increases when global risk is perceived as low and falling.

5 Conclusion

The financial sector plays a pivotal role in the macroeconomy, as has become increasingly apparent since the financial crisis in 2008, and since then, many researchers have contributed to the literature explaining the links between the two. We contribute to this literature by focusing on economic agents' attitudes towards risk as an essential driver of economic growth. To this end, we construct a Bayesian learning model for how observations of risk affect the agents' posterior belief of the state of the risk cycle. While the posterior is not directly observable, we proxy it by the duration of low risk (DLR). We then use a panel of 73 countries since 1900 to map the rises and falls in agents' perceptions of risk onto contemporaneous and future economic growth.

We show that perception of high-risk has an unambiguous negative short-term impact on growth, as expected. By contrast, a lengthening of the low-risk phase has a longer-term effect: initially positive but eventually followed by a reversal (a boom-to-bust cycle). Low-risk environments increase the optimism and agents' willingness to take on more risk, boosting investment and growth in the short-to-medium term at the cost of increasing financial leverage, eventually followed by a reversal. Overall, on aggregate, low-risk perceptions are followed by higher growth, with two exceptions being excessive credit growth and very long-lasting low-risk environments. In these cases, the amplitude of the reversal in growth is stronger and longer-lasting than would otherwise be, with an overall negative impact on growth.

The global risk perceptions are particularly important in shaping local business cycles, affecting the investment decisions of both domestic and global investors, and they are manifested via three main channels: investments, capital flows, and the riskiness of bond issuance. Furthermore, risk perceptions in the United States play a pivotal role in economic outcomes throughout the world.

Our results contribute to several important policy debates. Consider macroprudential regulations. After the crisis of 2008, policymakers, justifiably intent on preventing a repeat, have been actively aiming to reduce the amount of risk financial institutions can take — *de-risking* the financial system. In other words, they want to reduce their risk by requiring higher levels of capital and imposing stringent lending standards. While such de-risking promises to reduce the likelihood of a costly financial crisis, our findings show that it may reduce economic growth. The aggregate impact of a low-for-long volatility environment on growth depends on the prevailing level of financial vulnerabilities. When such vulnerabilities increase, such as in the form of excess non-financial sector credit, the economy is expected to be more fragile and less resilient to adverse shocks. Our results point to the importance of policymakers considering the joint impact of macroprudential and monetary policies on the likelihood of crises and growth.

Our results also demonstrate the limit to monetary policy independence, especially when intended to use for macroeconomic objectives, almost always mandated in central bank legislation. Even if a domestic monetary authority intends to either stimulate or cool down its national economy by affecting the price and quantity of money, global risk perceptions and risk-taking incentives in financial markets can override national monetary policy decisions. After all, the global risk cycle affects capital flows, investment decisions, and credit conditions. This cycle is driven by the length of a low-risk environment and its effect on domestic economic growth is significantly higher than that of domestic risk perceptions.

Our final policy conclusion focuses on the importance of global institutions like the IMF, the World Trade Organization, and the Financial Stability Board. Their tasks of enhancing the efficiency of the global financial and economic systems are important. Individual countries cannot ignore the global risk environment, however much they might want to because it contributes more strongly to the risk appetite of domestic agents than does their local risk environment. That consideration is especially important for emerging countries, those without deep domestic financial markets.

Appendix A: Sample details

Table A1: Sample details

This table lists the countries in our sample, whether they are developed or emerging markets based on the International Monetary Fund classification, sample coverage, and the names of the market indexes. We report the name of the market index used at the end of the sample period. Given the long historical data, it is not possible to list all of the indexes used for all countries. For example, for the U.S., between 1900 to 1923, the Cowles Commission's back-calculated composite of stocks is used. After 1923, S&P is used. See GFD for details. Source: Global Financial Data.

Country	Classification	Coverage	Market
Argentina	Emerging	Jan. 1956–June 1958/	Argentina Swan, Culbertson and Fritz/
		Dec. 1966–Dec. 2016	Buenos Aires SE General (IVBNG)
Australia	Developed	Jan. 1900–Dec. 2016	Australia ASX All-Ordinaries
Austria	Developed	Jan. 1941–Dec. 2016	Wiener Boersekammer Share (WBKI)
Bahrain	Emerging	June 1990–Dec. 2016	Bahrain BSE Composite
Bangladesh	Emerging	Jan. 1990–Dec. 2012	Dhaka SE General
Belgium	Developed	Jan. 1900–Dec. 2016	Brussels All-Share Price
Brazil	Emerging	Jan. 1955–Feb. 2000/	Rio de Janeiro Bolsa de Valores (IBV)
Bulgaria	Emerging	Oct. 2000–Dec. 2016	SE SOFIX
Canada	Developed	Jan. 1915–Dec. 2016	Canada S&P/TSX 300 Composite
Chile	Emerging	Jan. 1927–Dec. 2016	Santiago SE General (IGPA)
China	Emerging	Jan. 1994–Dec. 2016	Shanghai SE Composite
Colombia	Emerging	Jan. 1927–Dec. 2016	Colombia IGBC General
Costa Rica	Emerging	Dec. 1994–Dec. 2016	Costa Rica Bolsa Nacional de Valores
Cote d'Ivoire	Emerging	Jan. 1996–Dec. 2016	Cote d'Ivoire Stock Market
Croatia	Emerging	Jan. 1997–Dec. 2016	Croatia Bourse (CROBEX)
Denmark	Developed	Jan. 1921–Dec. 2016	OMX Copenhagen All-Share Price
Ecuador	Emerging	Jan. 1994–Dec. 2016	Ecuador Bolsa de Valores de Guayaquil
Egypt	Emerging	Jan. 1950–Sept. 1962/	Egyptian SE/
		Dec. 1992–Dec. 2016	Cairo SE EFG General
El Salvador	Emerging	Jan. 2004– Dec. 2014	El Salvador Stock Market
Finland	Developed	Jan. 1920–Dec. 2016	OMX Helsinki All-Share Price
France	Developed	Jan. 1900–Dec. 2016	France CAC All-Tradable
Germany	Developed	Jan. 1900–Dec. 2016	Germany CDAX Composite
Ghana	Emerging	Nov. 1990–Oct. 2016	Ghana SE Databank/
			Ghana SE Composite
Greece	Developed	Dec. 1946–Dec. 2016	Athens SE General
Hungary	Emerging	Dec. 1924–Mar. 1948/	Hungary Stock Market/
		May 2002–Dec. 2016	OETEB Hungary Traded

Table A1: Sample details (cont.)

Country	Classification	Coverage	Market
Iceland	Developed	Dec. 1992–Dec. 2016	OMX Iceland All-Share Price
India	Emerging	Jan. 1922–Dec. 2016	Bombay SE Sensitive
Indonesia	Emerging	Jan. 1983–Dec. 2016	Jakarta SE Composite
Iran	Emerging	Mar. 1990–Dec. 2016	Tehran SE Price (TEPIX)
Ireland	Developed	Jan. 1934–Dec. 2016	Ireland ISEQ Overall Price
Italy	Developed	Sept. 1905–Dec. 2016	Banca Commerciale Italiana
Japan	Developed	July 1914–Dec. 2016	Tokyo SE Price (TOPIX)
Kazakhstan	Emerging	July 2000–Dec. 2016	Kazakhstan SE KASE
Kenya	Emerging	Jan. 1964–Dec. 2015	Nairobi SE
Korea	Developed	Jan. 1962–Dec. 2016	Korea SE Stock Price (KOSPI)
Kuwait	Emerging	Oct. 1996–Dec. 2016	Kuwait SE Index
Luxembourg	Developed	Oct. 1954–Dec. 2016	LuxSE
Malaysia	Emerging	Dec. 1973–Dec. 2016	Malaysia KLSE Composite
Malta	Emerging	Dec. 1996–Dec. 2016	Malta SE
Mauritius	Emerging	July 1989–Dec. 2016	SE of Mauritius (SEMDEX)
Mexico	Emerging	Jan. 1931–Dec. 2016	Mexico SE Indice de Precios y Cotizaciones
Mongolia	Emerging	Aug. 1995–Dec. 2016	Mongolia SE Top-20
Montenegro	Emerging	Mar. 2003–Dec. 2016	Montenegro NEX-20
Morocco	Emerging	Jan. 1988–Dec. 2016	Casablanca Financial Group 25 Share
Netherlands	Developed	Jan. 1919–Dec. 2016	Netherlands All-Share Price
New Zealand	Developed	Jan. 1931–Dec. 2016	New Zealand SE All-Share Capital
Nigeria	Emerging	Jan. 1988–Dec. 2016	Nigeria SE
Norway	Developed	Jan. 1914–Dec. 2016	Oslo SE OBX-25 Stock
Pakistan	Emerging	July. 1960–Dec. 2016	Pakistan Karachi SE-100
Panama	Emerging	Dec. 1992–Dec. 2016	Panama SE (BVPSI)
Paraguay	Emerging	Oct. 1993–Sept. 2008	PDV General
Peru	Emerging	Jan. 1933–Dec. 2016	Lima SE General
Philippines	Emerging	Dec. 1952–Dec. 2016	Manila SE Composite
Poland	Emerging	Jan. 1921–Dec. 1939/ Apr. 1994–Dec. 2016	Warsaw SE 20-Share Composite/
Portugal	Developed	Jan. 1933–Dec. 2016	Oporto PSI-20
Qatar	Emerging	Dec. 1995–Dec. 2016	Qatar SE
Russia	Emerging	Jan. 2002–Dec. 2016	Russia AK&M Composite (50 shares)
Saudi Arabia	Emerging	Feb. 1985–Dec. 2016	Saudi Arabia Tadawul SE
Singapore	Developed	July 1965–Dec. 2016	Singapore FTSE Straits-Times
South Africa	Emerging	Jan. 1910–Dec. 2016	FTSE/JSE All-Share
Spain	Developed	Dec. 1914–Dec. 2016	Madrid SE General

Table A1: Sample details (cont.)

Country	Classification	Coverage	Market
Sri Lanka	Emerging	Dec. 1984–Dec. 2016	Colombo SE All-Share
Sweden	Developed	Jan. 1906–Dec. 2016	Sweden OMX Affärsvärldens General
Switzerland	Developed	Jan. 1921–Dec. 2016	Switzerland Price
Thailand	Emerging	Apr. 1975–Dec. 2015	Thailand SET General
Tunisia	Emerging	Dec. 1997–Dec. 2016	Tunisia SE
Turkey	Emerging	Jan. 1986–Dec. 2016	Istanbul SE IMKB-100 Price
Ukraine	Emerging	Jan. 1998–Dec. 2016	Ukraine PFTS OTC
United Arab Emirates	Emerging	Oct. 2004–Dec. 2016	Abu Dhabi All-share
United Kingdom	Developed	Jan. 1900–Dec. 2016	UK FTSE All-Share
United States	Developed	Jan. 1900–Dec. 2016	S&P 500 Composite Price
Venezuela	Emerging	Jan. 1937–Dec. 2015	Caracas SE General
Zambia	Emerging	Dec. 1996–Dec. 2016	Zambia Lusaka All-Share (LASI)

Appendix B: Data definitions and sources

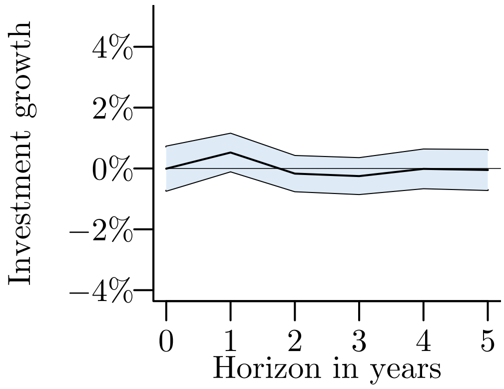
- $\text{DLR}_{i,t}$: Duration of low risk, calculated as in (9). It considers the consecutive number of years in which stock market volatility remains low for country i in year t with decaying weights. Volatility (VOLA) is annual realized volatility–the standard deviation of real monthly stock market returns over a year. Monthly stock market indexes are collected from Global Financial Data (GFD), with data available for 73 countries, spanning 1900 to 2016. Data coverage is listed in Table A1.
- G-DLR_t: Global DLR is calculated as the GDP-weighted cross-sectional averages of local DLRs ($\text{DLR}_{i,t}$).
- $\text{DHR}_{i,t}$: Duration of high risk. Calculated analogous to $\text{DLR}_{i,t}$ and considers the consecutive number of years in which stock market volatility remains high for country i in year t.
- G-DHR_t: Global DHR is calculated as the GDP-weighted cross-sectional averages of local DHRs ($\text{DHR}_{i,t}$).
- GDP growth: Log-real GDP growth rate. Annual GDP per capita and population numbers are from the Maddison (2003) database, available at `http://www.ggdc.net/maddison/`. Data from the Maddison project cover 72 countries from 1900 to 2016.
- Log GDP: log per-capita income. Data from the Maddison project cover 72 countries from 1900 to 2016.
- INF: The inflation rate is calculated as the annual percentage change of the consumer price index. Data are from the GFD.

- POLCOMP: Political competition as a proxy for institutional quality. Data are from the Polity IV Project database. POLCOMP is the combination of the degree of institutionalization or regulation of political competition and the extent of government restriction on political competition. The higher the value of the POLCOMP, the better the institutional quality of a given country.
- Δ STIR: Change in short-term interest rates. Three-months Treasury Bill yields, from the GFD from 1900.
- ΔXR: Change in exchange rates, local currency with respect to U.S. dollar. Data from the GFD.
- TERM: Term premium, defined as the difference between the long-term and short-term interest rates, from GFD.
- DY: Dividend yields, from Baron and Xiong (2017).
- VIX: The CBOE Volatility Index.
- BEX: Bekaert et. al (2019)'s risk aversion measure
- PVS: Pflueger et. al (2020)'s PVS.
- Positive macro surprises: The average of the Scotti (2016) macroeconomic surprise index, provided that the index is positive.
- BEX uncertainty: Bekaert et. al (2019)'s uncertainty index.
- Liquidity shocks: The negative difference between Amihud's (2002) illiquidity measure and its past 12-month average.
- MP shocks: U.S. monetary policy shocks introduced in Romer and Romer (2004). The authors use the FED Greenbook forecasts of output growth and inflation along with the fed funds rates to estimate shocks. The sample covers 1970 to 2008.
- ΔFlows/GDP: Change in total portfolio inflows as a percentage of the local country's GDP, taken from the International Monetary Fund's Balance of Payments statistics (BPM5). The sample covers 55 countries from 1970 to 2012.
- Investment growth: Private investment growth is the first-log difference of gross capital formation (investment in fixed assets and inventory), as a percentage of GDP, obtained from the World Development Indicators for 1960 to 2012 and 73 countries.
- HY share: Lending standards are proxied via the high-yield bond issuance data constructed by Kirti (2020). Data cover 38 countries from 1980 to 2016.

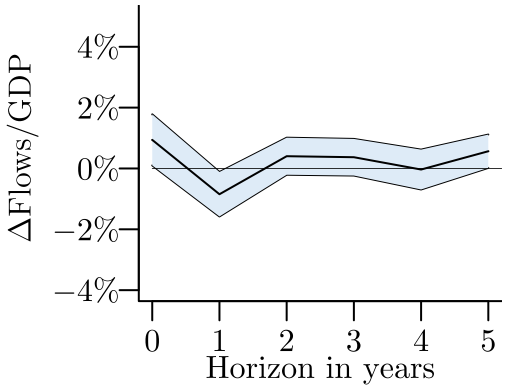
Appendix C

Figure C1: Impact of the perception of low risk on investment, capital flows, and lending standards.

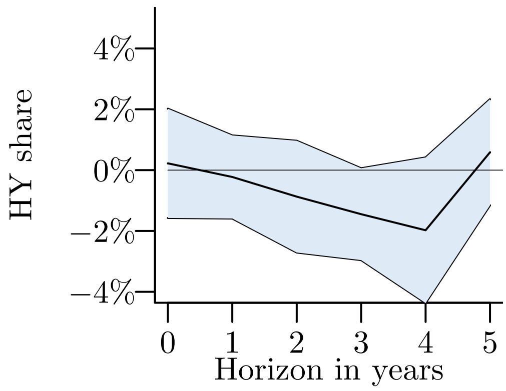
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of investment growth, changes in portfolio inflows, and lending standards to a shock to the local duration of low volatility (DLR), which is introduced in Section 2.2. Private investment is proxied by gross capital formation (investment in fixed assets and inventories), as a percentage of GDP, and we obtain the data from the World Development Indicators for 73 countries from 1960 to 2012. Total portfolio inflows data (as a percentage of GDP) are obtained from the International Monetary Fund for 55 countries from 1970 to 2012. Lending standards are proxied via the high-yield bond issuance data constructed by Kirti (2020). Data cover 38 countries from 1980 to 2016. We run regressions (12) by replacing growth, with capital flows, growth of investment, and the high-yield (HY) share index as dependent variables. All regressions include the lagged values of the inflation rate, the degree of political competition, log-GDP, change in short term interest rates, the dependent variable, duration of low risk (DLR), duration of high risk (DHR), their global counterparts (G-DLR and G-DHR), and country and decade fixed effects. We dually clustered standard errors at the country and year levels.



(a) Shock to local DLR



(b) Shock to local DLR



(c) Shock to local DLR

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Table 1: Correlations of DLR and G-DLR with other risk perception measures
Panel A of this table presents the Pearson correlation coefficients between U.S. duration of low risk (US-DLR) and listed risk perception proxies specified in the last column. Specifically, we include the CBOE Volatility Index (VIX) index, the risk aversion measure (BEX) of Bekaert et al. (2019) and the price of volatile stocks (PVS) of Pflueger et al. (2020). We also consider the net percentage of U.S. banks reporting increased demand and tightening lending standards both obtained from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS). Finally, the last row use the default spread measured as the difference between BAA and AAA corporate bond spreads from the Federal Reserve Bank of St Louis. Panel B presents the results of a panel regression model of real returns on DLR, dividend yields (DY), realized volatility (VOLA), inflation (INF), degree of political competition (POLCOMP), changes in short-term interest rates (ΔSTIR), term premium (TERM), and GDP level. We obtained data from the Global Financial Data, Maddison (2003), Polity IV, and Baron and Xiong (2017). All variables used are defined in Appendix B. Country and year fixed effects are included in the specification. For the sake of brevity, only the estimated coefficients of DLR are presented.***, **, and * denotes significance at the 1%, 5%, and 10% levels. The standard errors are robust and dually clustered at the year and country level.

Panel A: Pearson correlations

	Number of Obs.	Correlation with US-DLR	Risk perception measures
1	25	-0.751***	VIX
2	28	-0.558***	BEX
3	45	0.357**	PVS
4	24	0.442**	net % of banks reporting increased demand
5	25	-0.528***	net % of banks reporting tightening standards
6	45	-0.400***	Default spread (BAA-AAA)

Panel B: DLR and real returns
Dependent variable: $R_{i,t}$

	Coefficient estimate	Standard error
$\text{DLR}_{i,t}$	1.264**	0.607
$\text{DY}_{i,t}$	-6.994***	2.456
$\text{VOLA}_{i,t}$	6.363**	2.855
$\text{INF}_{i,t}$	-0.507***	0.069
$\text{POLCOMP}_{i,t}$	0.546	1.423
$\text{GDP}_{i,t}$	-1.666	1.433
$\Delta\text{STIR}_{i,t}$	-0.190**	0.058
$\text{TERM}_{i,t}$	-1.630	1.854
Adj. R^2	0.123	
Nº Obs.	1,084	

Table 2: Why does DLR vary?

This table reports the results of simple regressions of U.S. DLR on (1) positive macroeconomic news surprises, (2) uncertainty shocks, (3) liquidity shocks, and (4) monetary policy shocks (MP shocks). To obtain positive macroeconomic surprises, in a given year, we calculate the average value of the Scotti (2016) macroeconomic surprise index, provided that the index is positive. BEX uncertainty is the Bekaert et al. (2019) uncertainty index. Following Bali et al. (2014), we define liquidity shocks as the difference between stock market turnover and its past 12-month average. Finally, MP shocks are the monetary policy shocks of Romer and Romer (2004). All variables are defined in Appendix B. All variables are standardized to ease the interpretation. ***, **, and * denotes significance at the 1%, 5% and 10% levels, respectively. Newey-West (1987) standard errors with 5 lags are reported.

Dep. var. DLR_t	β	St. Error	Adj.R^2	N
Positive macro surprises$_t$	0.039**	(0.014)	0.063	24
BEX uncertainty$_t$	-0.081***	(0.020)	0.288	28
Liquidity shocks$_t$	0.023**	(0.011)	0.0231	130
MP shocks$_t$	0.060**	(0.027)	0.187	37

Table 3: The impact of global low risk on growth: Endogeneity concerns

In panel A, we report the results when using a two-stage regression approach in (13) and (14). In the first stage, we regress global duration of low risk (G-DLR) on lagged values of natural disasters, terrorist attacks, coups, and revolutions, U.S. liquidity shocks, and U.S. stock market realized volatility. Natural disasters, terrorist attacks, coups, and revolutions are obtained from Baker et al. (2020). We calculate the GDP-weighted cross-sectional averages to obtain the corresponding global shock. U.S. liquidity shocks are defined as the difference between the stock market turnover and its past 12-month average, per Bali et al. (2014). We report the F statistics and corresponding p-value. In the second stage, we regress growth on $\widehat{\text{G-DLR}}$, while controlling for the lagged values of $\widehat{\text{G-DLR}}$ and $\widehat{\text{G-DHR}}$ along with the rest of the control variables in the baseline specifications, but for the sake of brevity, estimated coefficients of control variables are omitted. In the first row of panel B, we report the estimated coefficients for G-DLR, when we alter the baseline specification (12) by including the news shock along with a G-DLR shock. In the second row, we further include the realized volatility shock. Finally, in the third row, we present the results for the (12) for the same sample period used in Panel B for comparison purposes. We follow the methodology proposed by Berger et al. (2020) to construct news shocks driven by implied volatility and orthogonal to current realized volatility innovations. For both panels, we bootstrap the standard errors with 1,000 sample draws clustering at the country and year level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively .

Panel A: Two-stage regression approach

	Second stage					
	h=0	h=1	h=2	h=3	h=4	h=5
$\widehat{\text{G-DLR}}$	0.246**	0.776***	-0.363***	-0.670***	-0.022	-0.007
	First stage					
	F-stat	p-value				
$\sum_{j=1}^{5}(\beta_j^{disasters} + \beta_j^{terror} + \beta_j^{coups} + \beta_j^{revolutions} + \beta_j^{LIQ} + \beta_j^{VOLA}) = 0$	3.64***	0.014				
Adj. R^2	0.66					

Panel B: News Shock approach

Shocks	h=0	h=1	h=2	h=3	h=4	h=5
G-DLR & News shock	0.531***	1.036***	-0.805***	-0.186	0.062	-0.181*
G-DLR & News shock & RV shock	0.532***	0.950***	-1.125***	0.175	0.182	-0.210
G-DLR	0.366***	0.832***	-0.714***	-0.257**	-0.029	-0.055

Table 4: Why does low risk cause a boom-to-bust cycle? Endogeneity concerns
In panel A, we report the results when using a two-stage regression approach. We use the first stage described in Table 3 and estimate $\widehat{\text{G-DLR}}$. In the second stage, we regress investment growth, changes in portfolio flows, and high yield share of issuance on $\widehat{\text{G-DLR}}$, while controlling for the lagged values of $\widehat{\text{G-DLR}}$ and $\widehat{\text{G-DHR}}$ along with the rest of the control variables in the baseline specifications. For the sake of brevity, estimated coefficients of control variables are omitted. In Panel B, we allow the presence of simultaneous news and G-DLR shocks in our baseline setting (12). We replace the endogenous variable economic growth with the growth of investment, changes in portfolio flows, and high-yield share index as dependent variables and keep the same control variables. We follow the methodology proposed by Berger et al. (2020) to construct news shocks driven by implied volatility and orthogonal to current realized volatility innovations. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. We bootstrap the standard errors with 1,000 sample draws clustering at the country and year level.

Panel A: Two-stage regression approach

	Second stage					
Dep. Var	h=0	h=1	h=2	h=3	h=4	h=5
Investment growth	0.436	0.716**	0.418	-1.006***	-1.205***	-0.289
ΔFlows/GDP	0.908***	-0.900***	-0.121	0.467	-0.273	0.164
HY share	1.913*	3.177***	0.128	-1.950**	-1.813	0.180

Panel B: News Shock approach

Shocks: G-DLR & News shock

Dep. Var	h=0	h=1	h=2	h=3	h=4	h=5
Investment growth	0.664**	1.750***	-0.112	-1.031***	-0.801**	0.126
ΔFlows/GDP	1.426***	-1.358***	0.707*	0.638	-0.743*	1.658***
HY share	3.168***	1.220	-0.287	-1.391	-1.680	-0.103

Table 5: Robustness

This table presents the robustness analysis. In the first column, we report whether the shock is to the global or local duration of low risk (G-DLR and DLR). In the second column, we report the type of robustness check. The rest of the columns report the estimated impulse responses for $h = 0$ to $h = 5$. In the first set of robustness tests, we employ the method proposed by Hamilton (2018) instead of the HP filter to estimate the trend and when the smoothing parameter of the HP filter is set to 1000 and 10000 instead of 5000. In addition, we estimate the low volatility state if the current country's volatility is below the one-standard-deviation band, respectively. Second, we estimate volatility as the sum of absolute monthly returns and also use nominal returns instead of real returns. Third, we examine our findings when the parameter θ is equal to 0.85 and 0.95 in equation (9) and when we do not apply any decaying factor and instead we count the number of consecutive years in which a country experiences a low volatility regime. We also consider the intensity of the deviations of volatility from its trend and calculate DLR as the sum of the volatility deviations when a country stays in a low volatility regime consequently. Fourth, we obtain G-DLR from a balanced panel using G7 countries and using only DLR of the United Stated. Fifth, we include credit spreads (Credit spr), change in exchange rates (ΔXR), the monetary policy surprise series from Romer and Romer (2004) (MPshock), the economic policy uncertainty (EPU) index of Baker et al. (2016) and the geopolitical risk index (GPR) of Caldara and Iacoviello (2018) in the control set. Sixth, we use 5 years and 20 years fixed effects instead of decade fixed effects and robust Driscoll Kraay standard errors. In the final set of robustness, we examine our results for the post–World War II period (1946–2016), the post–Bretton Woods period (1972–2016) and for emerging countries and for developed countries in the post–Bretton Woods period. All regressions include the lagged values of the inflation rate, the degree of political competition, log-GDP, change in short term interest rates, the dependent variable, duration of low risk (DLR), duration of high risk (DHR), their global counterparts (G-DLR and G-DHR), and country and decade fixed effects. We dually clustered standard errors at the country and year levels except when using Driscoll Kraay standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Shock	Robustness	h=0	h=1	h=2	h=3	h=4	h=5
1	G-DLR	Baseline	5.925***	9.728***	-7.803***	-2.670	-0.537	-1.077
2	DLR	Baseline	2.222***	3.282***	-2.141*	-0.231	1.199	-0.167
3	G-DLR	Hamilton	4.970***	8.617***	-6.122**	-1.039	-1.629	-1.756
4	DLR	Hamilton	1.902***	2.986***	-0.900	-0.217	0.968	-0.253
5	G-DLR	$\lambda = 1000$	6.182***	11.876***	-7.312**	-3.741	-1.593	-0.725
6	DLR	$\lambda = 1000$	1.958***	2.714***	-1.739**	-0.503	0.739	-0.280
7	G-DLR	$\lambda = 10000$	5.502***	10.078***	-7.291**	-3.245	-0.424	-1.133
8	DLR	$\lambda = 10000$	2.161***	2.847***	-2.049*	-0.377	1.214*	0.001
9	G-DLR	one st. dev. band	38.655**	21.628	-73.529**	-60.962*	-17.905	-17.682
10	DLR	one st. dev. band	2.646*	3.174	1.736	1.264	5.061***	0.757
11	G-DLR	Abs. ret.	7.875***	10.804***	-8.076**	-4.376	-0.849	-1.214
12	DLR	Abs. ret.	2.522***	3.004***	-2.772***	-0.246	0.721	0.082
13	G-DLR	Nominal	6.637***	9.859***	-7.953**	-3.931	0.102	-1.173
14	DLR	Nominal	2.029***	2.671***	-1.257	-0.139	1.601**	-0.099

Table 5: Robustness (cont.)

	Shock	Robustness	h=0	h=1	h=2	h=3	h=4	h=5
15	G-DLR	$\theta = 0.85$	3.457***	7.096***	-5.548***	-2.406	-0.393	-0.717
16	DLR	$\theta = 0.85$	1.310**	2.376***	-1.572*	-0.285	0.960	-0.141
17	G-DLR	$\theta = 0.95$	8.143***	16.609***	-13.601***	-5.843	-0.671	-1.841
18	DLR	$\theta = 0.95$	2.870*	5.391***	-3.703*	-0.343	2.291*	-0.214
19	G-DLR	no decay. weights	0.447***	0.738***	-0.627***	-0.208	-0.027	-0.086
20	DLR	no decay. weights	0.156**	0.237***	-0.157*	0.002	0.092	-0.009
21	G-DLR	Intensity	19.234***	41.625***	-26.849**	-14.073	-2.532	-10.462*
22	DLR	Intensity	4.873**	9.089***	-5.494	0.021	1.161	-0.266
23	G-DLR	Balanced G7	6.353***	14.610**	-16.641***	-4.707	6.471	5.946
24	DLR	Balanced G7	0.425	2.495	-2.100*	-1.193	0.346	0.425
25	G-DLR	G-DLR US	3.745***	5.529***	-3.795**	-2.053	0.880	-0.341
26	DLR	G-DLR US	2.356**	3.940***	-1.701	-0.285	1.229	0.167
27	G-DLR	Credit spr	5.437***	9.565***	-8.570***	-1.859	-0.451	-1.968
28	DLR	Credit spr	2.133***	3.108***	-2.279**	-0.051	1.084	-0.247
29	G-DLR	ΔXR	5.930***	9.982***	-7.755***	-1.898	0.021	-0.788
30	DLR	ΔXR	1.739*	3.847***	-2.276*	-0.282	0.951	-0.229
31	G-DLR	MPshock	4.822***	9.285***	-8.915***	0.695	0.649	-1.775
32	DLR	MPshock	1.846**	2.617***	-1.916*	0.918	1.406*	-0.070
33	G-DLR	EPU&GPR	5.393***	7.583***	-9.345***	1.051	3.859**	-0.659
34	DLR	EPU&GPR	1.966***	2.407***	-2.180**	0.550	2.095***	0.179
35	G-DLR	5year FE	8.277***	8.738***	-9.848***	0.010	1.805	-3.209
36	DLR	5year FE	2.487***	2.676***	-2.304**	0.512	1.890**	-0.351
37	G-DLR	20year FE	5.523***	9.997***	-6.520**	-1.783	0.598	-0.437
38	DLR	20year FE	2.185**	3.543***	-1.679	0.125	1.563*	0.025
39	G-DLR	DriscollKraay	5.925***	9.728***	-7.803***	-2.670	-0.537	-1.077
40	DLR	DriscollKraay	2.222***	3.282***	-2.141	-0.231	1.199	-0.167
41	G-DLR	postWWII	5.854***	9.833***	-8.144***	-3.271	-0.466	-1.458
42	DLR	postWWII	2.097**	3.269***	-2.126*	-0.325	1.089	-0.233
43	G-DLR	postBW	6.007***	9.501***	-8.778***	-2.262	0.215	-1.799
44	DLR	postBW	2.320***	3.252***	-2.170	0.223	1.381*	-0.230
45	G-DLR	Emerging	0.723***	1.184***	-1.025***	-0.329	0.066	-0.427***
46	DLR	Emerging	0.483***	0.707***	-0.693***	-0.127	0.136	-0.089
47	G-DLR	Developed	0.541***	0.767***	-0.743***	-0.002	0.120	-0.008
48	DLR	Developed	0.231*	0.417**	-0.297	0.107	0.149	-0.094