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The Impact of Risk Cycles on Business Cycles: A Historical View

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We investigate the effects of financial risk cycles on business cycles, using a panel spanning 73 countries since 1900. Agents use a Bayesian learning model to form their beliefs about risk. We construct a proxy of these beliefs and show that perceived low risk encourages risk-taking, augmenting growth at the cost of accumulating financial vulnerabilities, and, therefore, a reversal in growth follows. The reversal is particularly pronounced when the low-risk environment persists and credit growth is excessive. Global risk cycles have a stronger effect on growth than local risk cycles via their impact on capital flows, investment, and debt-issuer quality. (*JEL* F30, F44, G15, G18, N10, N20)

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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

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matters. It is necessary for investment and growth but also drives uncertainty, inefficiency, recessions, and crises. While the interplay between financial risk and the 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 delaying investments (Dixit and Pindyck 1994; Bloom 2009; Bloom et al. 2018; Cascaldi-Garcia et al. Forthcoming). 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 of 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 that all risk measurements are inaccurate. Consequently, the degree of economic agents' beliefs in whether risk is high or low is of crucial importance to them. In our setting, the agents' risk beliefs are reinforced by 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 (Brunnermeier and Pedersen 2009; Scheinkman and Xiong 2003). Thus, beliefs, financial frictions, and risk-taking incentives interact: the willingness to take on more risk, increased asset prices, and 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 risk and leverage constraints binding (Greenwood and Hanson 2013; Adrian and Liang 2018). Depressed asset prices reduce the value of borrowers' assets, suppressing investment, as in Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999) and

[1] In Geanakoplos (2001) and 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) and Daníelsson, Shin, and Zigrand (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.

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, e.g., Schularick and Taylor 2012; Aikman et al. 2020). 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 in 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. 2022; Miranda-Agrippino and Rey 2020; Rey 2018; Jordà et al. 2019; Durdu, Martin, and Zer 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 consequently propose three channels through which global risk perceptions affect growth: 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 global financial conditions transmits to credit conditions and increases local lending and investment (Di Giovanni et al. 2022). 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 in which risk readings affect the agents' posterior belief that risk is 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 long time-series data, 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 stock market returns follow a stochastic volatility model containing 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 about the risk state to construct a posterior belief that risk is low or high. Their posterior beliefs drive their appetite for risk and, hence, their investment decisions. While we cannot directly estimate the agent's posterior beliefs, we know their 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 first measure risk with realized stock market volatility,[2] and then quantify what "low risk" is. The lower the volatility, the higher the chance that risk is low, and thus we identify periods of low risk when the estimated volatility is below a threshold. One can think of that threshold as "usual" risk, so agents alter their investment decisions when risk deviates from such levels, as in Keynes's (1936) animal spirits. The threshold cannot be constant across time and countries because the extant empirical evidence suggests that volatility has long volatility clusters, implying that a particular volatility reading might be seen as high risk in one state of the world and low in another. It is therefore necessary to model the threshold as a dynamic variable similar to how dynamic volatility is modeled. To that end, we use the historical volatility trend as the threshold in the baseline specifications. To estimate the trend, similar to our earlier work (Daníelsson, Valenzuela, and Zer 2018), we use a one-sided Hodrick and Prescott (1997) (HP) filter, using only past information to estimate the trend for a given time, necessary in our case because we run predictive regressions. In Section 3, we show that our main findings do not change when employing the linear projection method proposed by Hamilton (2018).

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

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2 Alternatively, we could have used corporate bond spread data since spreads are especially informative about credit conditions and the real macroeconomic outcomes Gilchrist, Yankov, and Zakrajšek (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, Siriwardane, and Sunderam's 2020).

Our empirical framework is impulse response functions obtained from Jordà's (2005) local projection method, which captures the impact of a 1-year increase in the persistence of low or high risk on growth, contemporaneously and up to 5 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 its local counterpart, with a cumulative contraction of 1.5%. 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 1 year hence, with a significant reversal in year 2. The impact of global DLR is about double the local counterpart. Even with a correction in year 2, a one-standard-deviation increase in global DLR increases economic growth by 0.7% across the boom-to-bust cycle. Thus, a low-risk environment has a cumulative positive impact on gross domestic product (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 that case, a shock to global DLR translates into a 0.65% contraction in 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 and reducing aggregate growth. 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, we employ a two-stage regression analysis similar to López-Salido, Stein, and Zakrajšek (2017). In the first stage, we regress G-DLR on a range of plausibly exogenous variables (including natural disasters 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, Dew-Becker, and Giglio (2020), derived from option prices and orthogonal to current realized volatility innovations. Our results continue to hold when we use either approach. 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 through which 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 G-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 2 to 4. 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 to 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 global risk. 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 International Monetary Fund (IMF) as developed or emerging, we find that the effects of global risk cycles on emerging countries' growth are higher than that of the local risk cycles and developed countries.

Taken together, we show that the perception of high risk has an unambiguous negative impact on growth, while perceived 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 those on macroprudential regulations, monetary policy independence, and the importance of the global risk environment. Policy makers 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, Veldkamp, and Venkateswaran (2020) model how agents form their beliefs, enabling tail events to trigger larger belief revisions. Meanwhile, Lochstoer and Muir (2022) 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, Stein, and Zakrajšek (2017) find that elevated credit sentiment in the United States harms growth, whereas stock market sentiment has no significant effect on growth. Pflueger, Siriwardane, and Sunderam's (2020) identify a positive relation between risk perception and investment. Our proposed measure, DLR, is closely related to other risk perception/appetite proxies, including Pflueger et al. (2020) price of volatility stocks (PVS). We then provide evidence that risk perceptions in stock markets are an important driver of economic fluctuations and risk cycles are not only restricted to the issuance and pricing of credit, as concluded by López-Salido et al. (2017).

Second, in earlier literature, Levine and Zervos (1998), Beck, Levine, and Loayza (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, Martin, and Zer (2020), Avdjiev et al. (2019), Rey (2018), and Jordà et al. (2019), focuses on the importance of the U.S. financial system driving the 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, we draw on the methodological contributions of our earlier work, Daníelsson, Valenzuela, and Zer (2018), in which we identify the importance of separating low 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, we underline the importance of the global risk environment. Finally, we show that different mechanisms are more 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) by showing an asymmetric impact of low and high risk on growth.

1. Data and Empirical Approach

1.1 Volatility, risk perception, and the duration of low risk

The extant literature shows that agents' perceptions of low or high risk alter their investment decisions (Caballero and Simsek 2020; Pflueger et al. 2020).

We capture the distinction between high and low risk with a binary variable that impacts volatility. Suppose the variance of financial returns (σ_t^2) follows a discrete stochastic volatility model with a first-order autoregressive process and a time-varying mean, similar to Hamilton (1989) and Danielsson (1994):

$$y = \sigma_t \epsilon_t, \ t=1,\cdots,T, \ \epsilon_t \sim N(0,1) \tag{1}$$

$$\log\sigma_t^2 = \gamma_0+\gamma_1 I_t+\beta\log\sigma_{t-1}^2+\eta_t, \ \eta_t \sim N(0,\zeta^2), \tag{2}$$

where I_t indicates whether the volatility state is high or low:

$$I_t = \begin{cases} 0 & \text{if } x_t = \text{Low} \\ 1 & \text{if } x_t = \text{High}. \end{cases} \tag{3}$$

x_t is an unobservable Markov switching binary state variable with symmetric transition probabilities q, where $q > 0.5$, so that the risk state is persistent, consistent with empirical observations of volatility clustering:

$$\Pr(x_{t+1} \mid x_t) = \begin{cases} q & \text{if } x_{t+1} = x_t \\ 1-q & \text{if } x_{t+1} \neq x_t. \end{cases} \tag{4}$$

Economic agents' investment decisions are based on the risk state and we capture the distinction between high and low risk with I_t. Furthermore, we assume $\gamma_1 > 0$, so that (2) implies that volatility decreases when the risk state is low. Although the risk state is latent, the agents observe volatility and use it to form their posterior probability of it. Specifically, the agents' signal is a transformation of volatility, which can be written as a noisy signal of the true risk state:

$$s_t = \frac{1}{\gamma_1}\left(\log\sigma_t^2 - \gamma_0 - \beta\log\sigma_{t-1}^2\right) = I_t + \frac{\eta_t}{\gamma_1}. \tag{5}$$

The agents start each year with a prior belief (α_t) about the current risk state. Conditional on having observed a history of signals, Bayesian updating implies that the posterior belief that the risk state is low ($\alpha_{t|t}$) is updated by:

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

$$= \frac{\phi\left(\frac{\gamma_1 s_t}{\zeta}\right)\alpha_t}{\phi\left(\frac{\gamma_1 s_t}{\zeta}\right)\alpha_t + \phi\left(\frac{\gamma_1 (s_t-1)}{\zeta}\right)(1-\alpha_t)}, \tag{7}$$

where $\phi(\cdot)$ is the standard normal density. Since η_t is normally distributed with mean 0 and variance ζ^2, $s_t|x_t = \text{Low} \sim N(0, \zeta^2/\gamma_1^2)$ and $s_t|x_t = \text{High} \sim N(1, \zeta^2/\gamma_1^2)$. The agents then use $\alpha_{t|t}$ to update their prior beliefs in the next year. Given the Markov transition probabilities, the prior belief in year $t+1$ is given by:

$$\alpha_{t+1} = q\alpha_{t|t} + (1-q)(1-\alpha_{t|t}). \tag{8}$$

The posterior probability $\alpha_{t|t}$ has three important properties. First, the lower the volatility shock η_t is, and thus the volatility, the higher the posterior probability of the risk state being low. Second, because volatility clusters (as $q>0.5$ and $\beta>0$), low-volatility states are more likely to be followed by low- than high-volatility states, ensuring that the signal s_t, and therefore $\alpha_{t|t}$, is persistent. Third, because the posterior is bounded at one, it increases at a decreasing rate with repeated low-volatility signals. The latter can also be observed in (8) above and (C10) and (C11) in Appendix C.

We cannot directly construct the posterior probability, as the model parameters are not observable to us. Consequently, we use (7) and (8) to construct a variable that proxies for the posterior probability of the risk state being low, what we term the "duration of low risk," DLR. Specifically:

$$\mathrm{DLR}_t = \frac{1-\theta}{\theta(1-\theta^{N+1})}\sum_{j=0}^{N}\theta^{j+1}\left(1-\mathbb{1}_{t-j}\right), \tag{9}$$

where the first term normalizes DLR so that it is bounded at one, N is the number of years the volatility state has been consecutively estimated as low, $0.5<\theta<1$, and $\mathbb{1}_t$ equals 1 if volatility is high, and 0 otherwise.

DLR encapsulates the key notions of $\alpha_{t|t}$: the lower the volatility is, the higher DLR becomes on average, and repeated observations of a low-risk state increase DLR at a decreasing rate. This is because DLR is a weighted average of low signals, where past observations are increasingly down-weighted. It is then straightforward to show that:

$$\mathrm{DLR}_t = [\theta \mathrm{DLR}_{t-1} + (1-\theta)(1-\mathbb{1}_t)](1-\mathbb{1}_t). \tag{10}$$

The persistence parameter θ captures the weight agents attach to historical observations when constructing their posterior beliefs. In order to see how θ is related to the model parameters, we use (7) and (8) to approximate θ as follows:

$$\theta \approx \frac{(2q-1)\phi_L}{(1-q)\phi_L + q\phi_H} - \frac{(1-q)\phi_L(2q-1)(\phi_L-\phi_H)}{((1-q)\phi_L + q\phi_H)^2}, \tag{11}$$

where $\phi_L = \phi\left(\frac{\gamma_1 s_t}{\zeta}\right)$ and $\phi_H = \phi\left(\frac{\gamma_1(s_t-1)}{\zeta}\right)$. See Appendix C for the derivation details.

In order to evaluate how accurately DLR proxies the posterior and to identify the appropriate values for θ, we calibrate the volatility model parameters to the mean, variance, skewness, and the first- and second-order autocorrelation of the annual S&P 500 index returns. We then use the calibrated parameters to simulate representative volatilities, thus ensuring that their time-series properties match those of the S&P 500. With the simulated volatilities in hand, we calculate the correlation between the posterior and DLR. We find that for $\theta \in (0.70, 1)$, the DLR-posterior correlation ranges from 0.70 to 0.95. Furthermore, we calculate the average θ implied from (11) and find that to be 0.92; we opt to use that value for our main analysis. The corresponding correlation between the posterior and DLR is 0.81 when $\theta = 0.92$, which is also consistent with the accurate weighing of historical annual volatility in volatility forecast models.[3]

The final step is the empirical estimation of DLR, which in turn depends on identifying the high- and low-volatility periods. It follows from (2) that if the volatility is very low, it is more likely that the volatility state is low and that volatility is below some threshold. In other words, when volatility (σ_t) is below a threshold (τ_t), we can classify the volatility state as low, and high otherwise. This identification is noisy, consistent with (5). The threshold cannot be constant across time and countries because volatility cycles are both long and asynchronous across countries. Consequently, a particular measurement of volatility might be seen as worryingly high in one country/time and as comfortably low in another. Ultimately, we need to estimate both the volatility and the threshold dynamically.

1.2 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.[4] To account for different inflation dynamics throughout time and across countries, we adjust nominal returns with the Consumer Price Index (CPI). In Section 3, 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 real macroeconomic outcomes (Gilchrist, Yankov, and Zakrajšek 2009), we could have used spread data to drive DLR. However, country-level historical cross-sectional data on bond spreads (including Treasury–corporate yield and high yield–investment grade yield spreads) are

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[3] The exponentially weighted moving average volatility model and (10) have a familiar functional form, not surprising as both models capture volatility clusters. The estimated persistence parameter in such volatility models is generally found to exceed 0.90, and hence is consistent with our chosen value for θ. As a further robustness check, we show in Section 3 that our main findings are robust to a wide range of θ 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.

[4] 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 1 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. (2021) 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.

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).[5] Hence, we estimate DLR using stock prices, given that it is more readily available in a consistent form in any country with a stock market.

Second, after calculating the realized volatility estimates, $\hat{\sigma}_{i,t}$, we obtain the low and high volatilities ($\hat{\sigma}_{i,t}^{\text{low}}$, $\hat{\sigma}_{i,t}^{\text{high}}$), analogous to receiving high and low signals in (5):

$$\begin{aligned} \hat{\sigma}_{i,t}^{\text{high}} &= \begin{cases} \hat{\sigma}_t - \hat{\tau}_{i,t} & \text{if} \quad \hat{\sigma}_t > \hat{\tau}_{i,t} \\ 0 & \text{otherwise,} \end{cases} \\ \hat{\sigma}_{i,t}^{\text{low}} &= \begin{cases} \hat{\sigma}_t - \hat{\tau}_{i,t} & \text{if} \quad \hat{\sigma}_t \leq \hat{\tau}_{i,t} \\ 0 & \text{otherwise,} \end{cases} \end{aligned} \tag{12}$$

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. We estimate the trend via a one-sided Hodrick and Prescott (1997) filter.[6]

$$\begin{aligned} \hat{\tau}_{i,t}(\lambda) = \min_{\{\tau_{i,t}(\lambda)\}_{t=1}^{T_i}} & \sum_{t=1}^{T_i} \left[\sigma_{i,t} - \tau_{i,t}(\lambda)\right]^2 \\ & + \lambda \sum_{t=2}^{T_i - 1} \left\{ \left[\tau_{i,t+1}(\lambda) - \tau_{i,t}(\lambda)\right] - \left[\tau_{i,t}(\lambda) - \tau_{i,t-1}(\lambda)\right] \right\}^2, \\ & \qquad i = 1, \ldots, N, \end{aligned} \tag{13}$$

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 1,600 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, Valenzuela,

[5] In addition, Gebhardt, Hvidkjaer, and Swaminathan (2005), Hong, Lin, and Wu (2012) find that stock returns have predictive power for bond returns as bond prices adjust more slowly than stock prices to information about changing default risk. Along similar lines, Downing, Underwood, and Xing (2009) show that the U.S. corporate bond market is less informationally efficient than the stock market.

[6] 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.

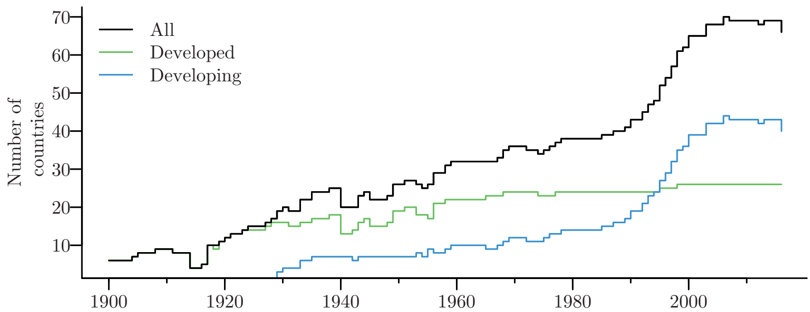

Figure 1
Data coverage
The number of countries with available stock market return data from 1900 to 2016. The classification into developed and developing is from the International Monetary Fund.

and Zer 2018), we set λ=5,000. In Section 3, we apply various smoothing parameters, concluding that the results are indifferent to the chosen parameter.

We collect monthly stock market indexes from Global Financial Data (GFD), with data available for 73 countries, from 1900 to 2016. On average, we have 55 years of observations 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, as shown in Figure 1. The number of countries increases steadily over time, (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.

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

Finally, we use the estimated low and high volatilities to calculate DLR and DHR. We present DLR and DHR estimates for each country in our sample in the internet Appendix.

1.3 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 (DLR$_{i,t}$) across all countries with data in year t. G-DHR$_t$ is calculated similarly.[7] The G-DLR measure in Figure 3 highlights NBER recession dates

[7] 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

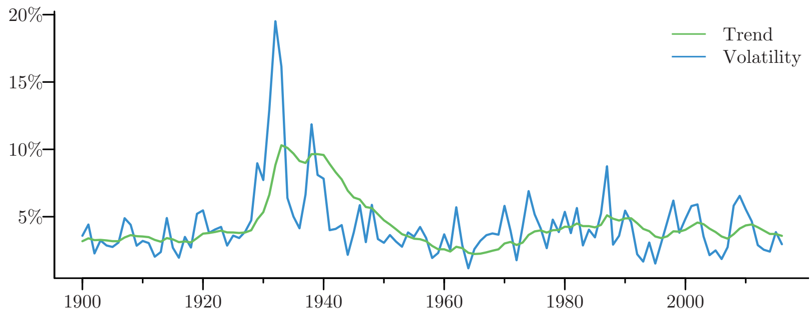

Figure 2
United States volatility and trend
Annual volatility and estimated trend for the United States. Volatility is calculated as the standard deviation of the previous 12 monthly real stock market returns. The trend is calculated by a one-sided Hodrick-Prescott filter with a smoothing parameter of λ=5,000.

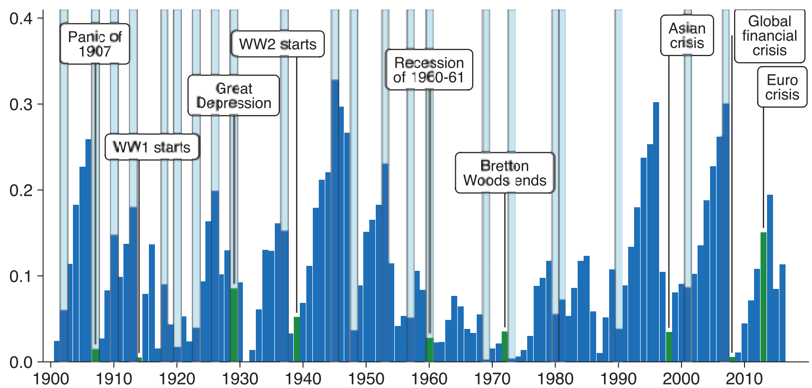

Figure 3
Global duration of low risk
The global duration of low risk (G-DLR$_t$) is calculated as the gross domestic product–weighted average of the local measure (DLR$_{i,t}$). DLR$_{i,t}$ is defined in (10), considering the consecutive number of years in which stock market volatility remains low for country i in year t with decaying weights. NBER recession dates are highlighted and relevant economic events are marked in the figure.

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 fall, but many of the countries with open stock markets in the sample were also occupied,

G7 constituents (United States, United Kingdom, France, Germany, Italy, Canada, and Japan). The results are presented in Section 3 and the main findings are robust.

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.

1.4 Assessing the validity of DLR as a risk perception measure

We assess the validity of our proposed measure, DLR, in three different ways. First, we expect DLR to be correlated to other proxies of risk perception and risk appetite, such as forward-looking volatility and various credit market indicators. Second, because a lower perception of risk should induce agents to take on more risk, we expect a higher DLR to increase the demand for stocks. 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 various proxies: The CBOE Volatility Index (VIX); Bekaert, Engstrom, and Xu's (2021) risk aversion measure (BEX); Pflueger, Siriwardane, and Sunderam's (2020) PVS; demand and credit standards of corporate loans from the Federal Reserve Board's Senior Loan Officer Opinion Survey; 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 0.35 to 0.74 (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. As 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 is 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 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.

Table 1
Correlations of DLR and G-DLR with other risk perception measures

A: Pearson correlations

	Number of Obs.	Correlation with US-DLR	Risk perception measures
1	25	-0.744^{***}	VIX
2	28	-0.555^{***}	BEX
3	45	0.354^{**}	PVS
4	24	0.438^{**}	net % of banks reporting increased demand
5	25	-0.523^{***}	net % of banks reporting tightening standards
6	45	-0.401^{***}	Default spread (BAA−AAA)

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

	Coefficient estimate	Standard error
$\text{DLR}_{i,t}$	1.297^{**}	0.602
$\text{DY}_{i,t}$	-6.997^{***}	2.459
$\text{VOLA}_{i,t}$	6.368^{**}	2.844
$\text{INF}_{i,t}$	-0.506^{***}	0.069
$\text{POLCOMP}_{i,t}$	0.540	1.423
$\text{GDP}_{i,t}$	−1.659	1.440
$\Delta\text{STIR}_{i,t}$	-0.190^{***}	0.058
$\text{TERM}_{i,t}$	−1.628	1.853
Adj. R^2	0.123	
No. Obs.	1,084	

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), the risk aversion measure (BEX) of Bekaert, Engstrom, and Xu's (2021), 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. Finally, the last row uses 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 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. The standard errors are robust and dually clustered at the year and country level. $^{*}p<.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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 and 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, Engstrom, and Xu's (2021) uncertainty index; liquidity shocks,

Table 2
Why does DLR vary?

Dependent variable: DLR_t	β	St. Error	Adj. R^2	N
Positive macro surprises$_t$	0.032**	(0.012)	0.063	24
BEX uncertainty$_t$	−0.067***	(0.017)	0.285	28
Liquidity shocks$_t$	0.019*	(0.010)	0.022	130
MP shocks$_t$	0.050**	(0.023)	0.184	37

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. (2021) 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. The sample size is determined by the availability of the particular measure. All variables are standardized to ease the interpretation. Newey-West (1987) standard errors with five lags are reported. $^{*}p<.1$; $^{**}p<0.05$; $^{***}p<0.01$.

as in Bali et al. (2014); and Romer and Romer's (2004) monetary policy shocks.[8]

We show the univariate regression results in Table 2. Positive macroeconomic news is associated with falling risk perceptions (higher DLR) as the expectations of consumers and investors adjust following good news arrivals (Forni, Gambetti, and Sala 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.

2. Empirical Methodology and Results

2.1 Econometric setup

Our main empirical device is impulse responses obtained from Jordà'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:

$$\begin{aligned}\Delta y_{i,t+h} = {} & \beta^h S_{i,t} + \textstyle\sum_{k=1}^{L} \delta_k^h \Delta y_{i,t-k} + \textstyle\sum_{k=1}^{L} \phi_k^h X_{i,t-k} \\ & + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}, \qquad (14) \\ h = {} & 0,\ldots,5,\end{aligned}$$

[8] 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, Engstrom, and Xu's (2021) 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.

$$S_{i,t} = \mathrm{DLR}_{i,t} \vee \text{G-DLR}_t \vee \mathrm{DHR}_{i,t} \vee \text{G-DHR}_t,$$

where $\Delta y_{i,t+h} = y_{i,t+h} - y_{i,t+h-1}$ with $y_{i,t}$ as the log-GDP of each country in the sample. We obtain annual GDP per capita 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.[9] 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, Valenzuela, and Zer (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 log per-capita income as a proxy for an aggregate financial development indicator (Levine and Zervos 1998; Levine 2006; Beck and Levine 2002) and changes in 3-month Treasury bill yields as short-term interest rates. Appendix B lists all variables used in the analysis, along with their definitions and data sources.

2.2 Risk cycles and growth

We start by investigating the effects of global and local risk cycles on business cycles. Although our 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 (14) contains 55 countries, spanning 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 by 0.8% over $h=0$ and $h=1$, whereas the economic impact of G-DHR is about double its local counterpart, with a cumulative contraction of 1.5%.

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 exacerbating information asymmetry problems, limiting credit available to firms (see Bloom et al. [2018], Dixit and Pindyck [1994], Ferreira

[9] 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 3, we include 5-year and 20-year fixed effects as robustness.

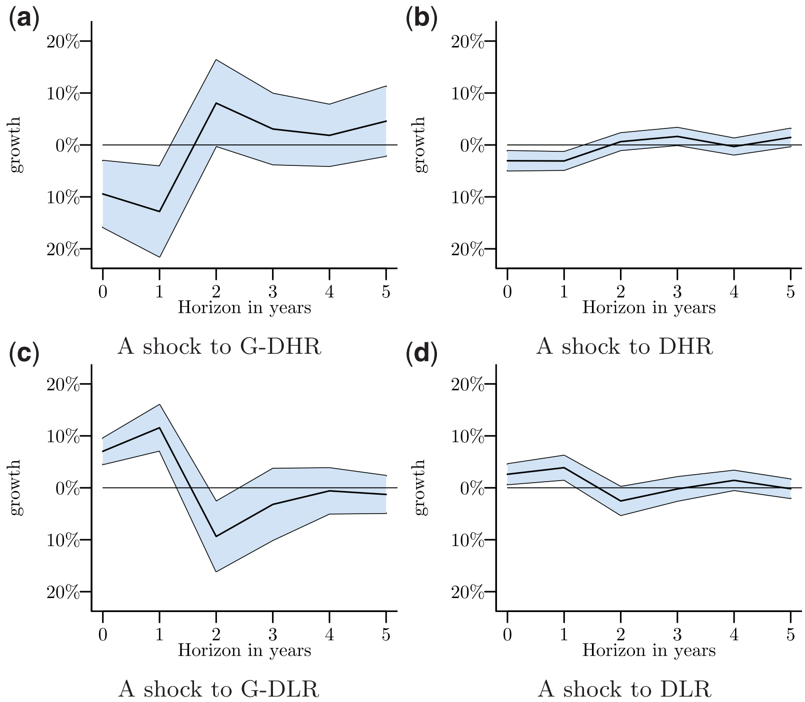

Figure 4
The impact of risk cycles on growth
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with their associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to the duration of high risk (DHR) and duration of low 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 1. In all cases, we run regressions (14) 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.

[2016], Gilchrist, Sim, and Zakrajšek [2014], and Cascaldi-Garcia et al. [Forthcoming] for a literature survey on uncertainty).

We then examine the effects of DLR on growth in panels (c) and (d). If its effects 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 quite 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 2 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 2 years, followed by a reduction of 0.8% in GDP growth. Overall, over the boom-to-bust cycle cumulatively, a one-standard-deviation increase in G-DLR increases GDP growth by about 0.7%. Furthermore, G-DLR has a stronger economic impact than its local counterpart in terms of its contribution to local growth: the amplitude of its boom-to-bust growth cycle is significantly higher than that of DLR. Our findings on the importance of G-DLR to local economic cycles are in line with those of Cesa-Bianchi, Pesaran, and Rebucci (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 in the country-specific output growth, compared to the proportion explained by the country-specific volatility shocks.

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.

2.3 Global low risk and growth: Endogeneity concerns

When running the regression in (14), 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) and 2) the news shock approach of Berger, Dew-Becker, and Giglio (2020).

In the first stage of the two-stage regression specification, we regress G-DLR on past values of a set of plausibly exogenous global variables, Z_t, that can affect agents' perceptions of risk. In particular, we include U.S. natural disasters, liquidity shocks, and realized volatility. We consider only U.S. series, rather than country-level data, to avoid the direct effects of natural disasters, liquidity, and volatility shocks on the local GDP growth. Natural disasters are from Baker, Bloom, and Terry (Forthcoming) since 1970. They include extreme weather events such as droughts, earthquakes, and floods obtained from the Center for Research on the Epidemiology of Disasters. Liquidity shocks are defined as the difference between the stock market turnover and its past 12-month average, as in Bali et al. (2014). Finally, we control for the U.S. stock market realized volatility, as it affects G-DLR by definition. We consequently run the following regression:

$$\text{G-DLR}_{i,t} = \theta + \sum_{k=0}^{1} \gamma_k Z_{t-k} + \epsilon_t. \tag{15}$$

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

A: Two-stage regression approach

	Second stage					
	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
$\widehat{\text{G-DLR}}$	0.556***	0.776***	−0.925***	−0.686***	−0.197	0.045
	First stage					
	F-stat	p-value				
$\sum_{j=0}^{1}(\beta_j^{\text{US nat. disasters}}+\beta_j^{\text{US LIQ}}+\beta_j^{\text{US VOLA}})=0$	15.07***	<0.01				
Adj. R^2	0.70					

B: News shock approach

Shocks	controls	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
G-DLR$_{\text{BDG}}$	baseline	0.095	0.507***	0.887***	−1.833***	−0.305	0.354
G-DLR$_{\text{BDG}}$	baseline + RV	0.113	0.522***	0.893***	−1.834***	−0.263	0.374

In panel A, we report the results when using a two-stage regression approach in (15) and (16). In the first stage, we regress the global duration of low risk (G-DLR) on U.S. natural disasters, U.S. liquidity shocks, and U.S. stock market realized volatility. Natural disasters are obtained from Baker et al. (Forthcoming). U.S. liquidity shocks are defined as the difference between stock market turnover and its past 12-month average, as in 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$_{\text{BDG}}$ when we alter the definition and calculate G-DLR by using the uncertainty shocks of Berger et al. (2020). In the second row, we further control for realized volatility. We follow the methodology proposed by Berger et al. (2020) to construct uncertainty 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. * $p<.1$; ** $p<0.05$; *** $p<0.01$.

For completeness, we also estimate the fitted estimate of G-DHR using (15). We then regress the GDP growth rate on $\widehat{\text{G-DLR}}$ controlling for the lagged values of $\widehat{\text{G-DLR}}$, $\widehat{\text{G-DHR}}$, along with the other variables used in our baseline specification (14). That is:

$$\Delta y_{i,t+h} = \beta^h \widehat{\text{G-DLR}}_t + \sum_{k=1}^{5} \delta_k^h \Delta y_{i,t-k} + \sum_{k=1}^{5} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}. \tag{16}$$

We report the results in Table 3, panel A. As we use estimated regressors 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 relation between the control set and G-DLR with an adjusted R^2 of 70% and an F-statistic over 15. 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 3. Even though this approach mechanically resembles an instrumental variables (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.

Second, we follow the methodology proposed by Berger, Dew-Becker, and Giglio (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 an identification problem, whereby we identify expected volatility shocks via a vector autoregression (VAR) model, and then orthogonalize them to current realized volatility innovations.

Implied volatility from options is highly informative about future realized volatility, so it is a natural state variable to include in the VAR, at least for the sample period for which we have data. As we need options markets data, for which long time horizons are only available in the United States, we focus on the United States from 1984 to estimate the uncertainty shocks. Accordingly, we first estimate a VAR model with the following moving average representation:

$$Y_t = (I - F(1))^{-1} C + B(L) A \varepsilon_t, \tag{17}$$

where

$$B(L) = \sum_{j=0}^{\infty} B_j L^j = (I - F(L))^{-1}. \tag{18}$$

Y_t includes stock market realized volatility, annualized 1-month implied volatility, changes in 3-month Treasury Bill rates, CPI inflation, and GDP growth rate, that is, $[RV_t, IV_t, \Delta STIR_t, INF_t, \Delta \log GDP_t]$. C denotes a vector of constants. $F(L)$ is a matrix of coefficients in the structural VAR setting, with the lag operator L. The shocks to realized volatility are ordered first and uncertainty shocks are ordered second in the structural VAR setting. The identifying assumption is that uncertainty news shocks do not affect realized volatility contemporaneously, but realized volatility can affect uncertainty.

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

$$E_t \sum_{j=1}^{n} RV_{t+j} - E_{t-1} \sum_{j=1}^{n} RV_{t+j} = \left(e_1 \sum_{j=1}^{n} B_j \right) A \varepsilon_t, \tag{19}$$

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 uncertainty news shock is obtained by orthogonalizing (19) with respect to the innovation to RV by following Barsky, Basu, and Lee (2015) and Barsky and Sims (2011).

We then use the estimated uncertainty shocks as an input, instead of using realized volatility, to calculate G-DLR in (10)—denoted as G-DLR$_{\text{BDG}}$. We report the estimated coefficients from specification (14) in Table 3, panel B, when we shock G-DLR$_{\text{BDG}}$ with and without controlling for realized volatility. As we use estimated regressors, we bootstrap the standard errors with 1,000 sample draws clustering at the country and year level. We confirm our main finding that global risk perceptions affect growth. Overall, these analyses increase our confidence in the effects of G-DLR on economic growth, although we remain cautious about the identification.

2.4 Risk perceptions, credit growth, and nonlinearities

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 in which 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, e.g., Schularick and Taylor 2012; Aikman et al. 2020). 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 depresses economic activity by amplifying the reversal in growth.

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

$$I_{i,t}^{q} := \begin{cases} 1 \ \text{ if credit growth}_{i,t} \geq \text{credit growth}_t^{q} \\ 0 \ \text{ otherwise,} \end{cases} \tag{20}$$

where credit growth$_t^{q}$ is the q_t^{th} 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 baseline impulse panel regressions in (14) to allow for two states, when credit is above or below the quantile q:

$$\begin{aligned} \Delta y_{i,t+h} = & \quad I_{i,t}^{q}\left(\beta^{h,\text{high}} S_t + \Gamma^{h,\text{high}} X_{i,t}\right) \\ & +(1-I_{i,t}^{q})\left(\beta^{h,\text{low}} S_t + \Gamma^{h,\text{low}} X_{i,t}\right) + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}, \qquad (21) \\ h = & \quad 0,\ldots,5, \\ S_t = & \quad \text{G-DLR}_t. \end{aligned}$$

$\beta^{h,\text{low}}$ 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

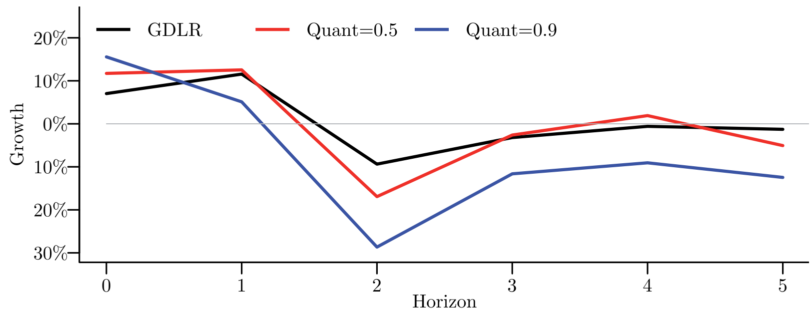

Figure 5
The impact of global low risk on growth, conditional on the state of the credit cycle
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with their associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to the global duration of low-risk (G-DLR) conditioning on excessive credit growth. G-DLR is introduced in Section 1. High credit growth is from (20), 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 (21) 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 in which 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.

(credit growth$_t^q$), 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 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 relation 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 3-year cycle.

Second, we extend (14) so that GDP growth is modeled as a third-degree polynomial in G-DLR:

$$\begin{aligned}\Delta_h y_{i,t+h} &= \beta_1^h \text{G-DLR}_{i,t} + \beta_2^h \text{G-DLR}_{i,t}^2 + \beta_3^h \text{G-DLR}_{i,t}^3 \\ &\quad + \sum_{k=1}^{L} \delta_k^h \Delta_h y_{i,t-k} + \sum_{k=1}^{L} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h},\end{aligned} \tag{22}$$

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 (22), we calculate the marginal rate of return of cumulative GDP growth to G-DLR as:

$$\rho(\widehat{\text{G-DLR}}) = \frac{\partial \Delta_h y}{\partial \text{G-DLR}} = \widehat{\beta_1^h} + 2\widehat{\beta_2^h}\text{G-DLR} + 3\widehat{\beta_3^h}\text{G-DLR}^2. \tag{23}$$

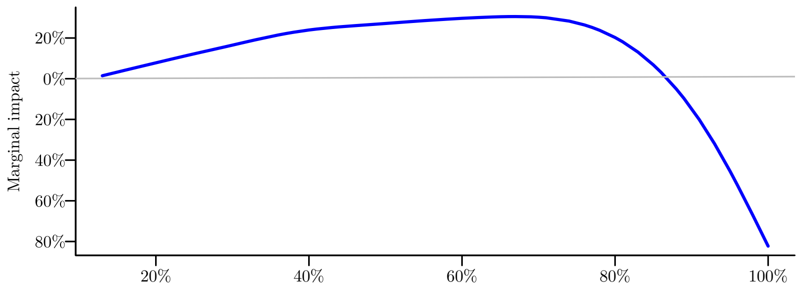

Figure 6
The nonlinear impact of G-DLR on growth
This figure shows the estimated marginal rate of return of cumulative GDP growth to G-DLR ($\widehat{\rho}$), introduced in (23). We plot $\widehat{\rho}$ at different quantiles of G-DLR. To estimate $\widehat{\rho}$, we run regression (22) so that cumulative GDP growth is modeled as a third-degree polynomial in G-DLR.

In Figure 6, we plot $\widehat{\rho}$ at different quantiles of G-DLR over the boom-to-bust cycle—that is, 2-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 an increase in DLR is concave.

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 the 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 5 consecutive years). Moreover, the episode was a clear example of increased vulnerabilities in the financial system: both corporate and particularly household lending was excessive. In this case, our analysis shows that the aggregate effect of G-DLR on growth was negative.

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

Why does perceived low risk affect economic growth? We surmise that 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 allow 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 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 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 include 38 countries with coverage going back to the early 1980s, primarily for advanced countries.

We run the baseline specifications (14) by replacing the endogenous variable with the growth of investment, capital flows, and high-yield share index while keeping the same controls.[10]

Figure 7 shows that G-DLR strongly affects investment, capital flows, and 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 0.5%, 1.3%, and 2.7%, but followed by a reversal of −1.8%, −1.3% and −1.1%, respectively. We then present the results for local DLR in Figure D1 in Appendix D, showing that it 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 Section 2.3 to alleviate possible endogeneity concerns. Table 4 shows that under both approaches there is a boom-to-bust cycle in investment, capital flows, and HY-share issuance following a shock in G-DLR. The timing of the cycles obtained via the former approach is in line with the main findings in Figure 7. Although we still find a boom-to-bust effect using the second approach, the results differ mainly due to the different sample periods.

3. Robustness

We execute 23 robustness tests, which can be classified into 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 linear projection method proposed

10 Because U.S. monetary policy decisions may also affect the relative return on investment in foreign economies, they 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.

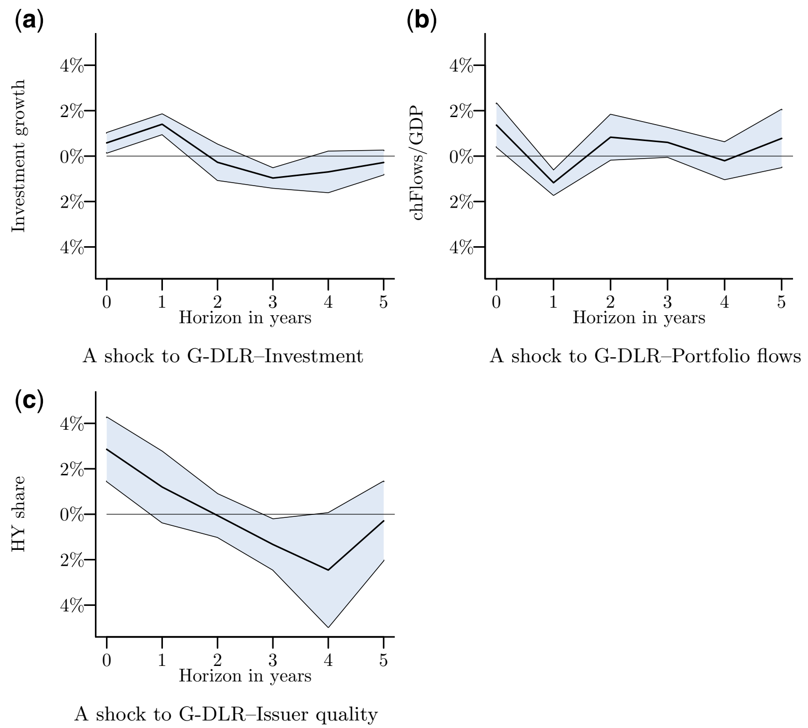

Figure 7
Impact of global low risk on investment, capital flows, and lending standards.
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with their associated 95% confidence band of investment growth, changes in portfolio inflows, and debt-issuer quality to a shock to the global duration of low risk –G-DLR, introduced in Section 1. 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 (14) 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.

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 (λ=1,000, λ=10,000, in addition to λ=5,000). We further employ a one-standard-deviation band instead of the HP filter trend by marking a low-volatility state if the current volatility is below its one-standard-deviation band.

Table 4
Why does low risk cause a boom-to-bust cycle? Endogeneity concerns

A: Two-stage regression approach

	Second stage					
Dep. Var	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
Investment growth	0.688**	1.124***	−0.563	−1.476***	−0.836**	0.330
ΔFlows/GDP	1.359***	−1.602***	−0.304	0.759*	−0.680	0.188
HY share	3.138***	1.362	−1.144	−1.785	−4.578**	0.296

B: News shock approach

Shocks: G-DLR$_{BDG}$						
Dep. Var	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
Investment growth	1.133***	−0.166	1.150**	−0.955	−1.476***	−1.284**
ΔFlows/GDP	−0.242	1.231**	−2.175***	1.894**	0.468	−1.053
HY share	3.973***	7.590***	−1.199	−2.797***	−1.660***	0.538

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 flow, 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, G-DLR$_{BDG}$ is calculated as in Table 3. We replace the endogenous variable economic growth with the growth of investment, changes in portfolio flow, and high-yield share index as dependent variables and keep the same control variables. We bootstrap the standard errors with 1,000 sample draws clustering at the country and year level. * $p<.1$; ** $p<0.05$; *** $p<0.01$.

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 (10), 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 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, Bloom, and Davis (2016), and geopolitical risk index (GPR) of Caldara and Iacoviello (2022). 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; 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. (2019) 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 also 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- 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 subperiods, market structures, developments, and types of countries. The structure of financial markets was quite different in 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 we do when there are many emerging countries in the sample, as seen in Figure 1.

The results are reported in Table 5. To ease their interpretation, instead of plotting impulse responses for all of the specifications, we present the estimated coefficients from (14) 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. 2019; Avdjiev et al. 2019).

Table 5
Robustness

	Shock	Robustness	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
1	G-DLR	Baseline	7.027***	11.562***	−9.369***	−3.196	−0.589	−1.279
2	DLR	Baseline	2.608***	3.873***	−2.540*	−0.221	1.432	−0.183
3	G-DLR	Hamilton	5.726***	9.952***	−7.264**	−1.109	−1.781	−1.992
4	DLR	Hamilton	2.159**	3.427***	−1.035	−0.223	1.131	−0.271
5	G-DLR	λ=1,000	6.795***	13.473***	−8.862**	−3.640	−1.610	−1.160
6	DLR	λ=1,000	2.316***	3.245***	−1.970*	−0.521	0.837	−0.385
7	G-DLR	λ=10,000	6.299***	11.251***	−8.230**	−3.479	−0.625	−1.476
8	DLR	λ=10,000	2.663***	3.438***	−2.351*	−0.473	1.356*	0.057
9	G-DLR	one st. dev. band	48.415**	26.716	−91.805**	−75.090*	−21.646	−21.089
10	DLR	one st. dev. band	3.260*	3.874	2.096	1.513	6.196***	0.988
11	G-DLR	Abs. ret.	9.280***	12.812***	−9.881***	−5.242	−0.906	−1.378
12	DLR	Abs. ret.	2.972***	3.560***	−3.345***	−0.255	0.868	0.152
13	G-DLR	Nominal ret.	7.899***	11.715***	−9.568**	−4.697	0.203	−1.304
14	DLR	Nominal ret.	2.368***	3.151***	−1.473	−0.129	1.938**	−0.112
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	7.582***	17.331**	−19.910***	−5.381	8.074	7.377
24	DLR	Balanced G7	0.495	2.965	−2.500*	−1.372	0.492	0.556
25	G-DLR	G-DLR US	4.516***	6.643***	−4.591**	−2.463	1.106	−0.393
26	DLR	G-DLR US	2.764**	4.661***	−2.013	−0.297	1.475	0.209
27	G-DLR	Credit spr	6.451***	11.393***	−10.233***	−2.216	−0.504	−2.356
28	DLR	Credit spr	2.502***	3.675***	−2.696**	−0.003	1.296	−0.279
29	G-DLR	ΔXR	7.042***	11.859***	−9.327***	−2.275	0.060	−0.947
30	DLR	ΔXR	2.035*	4.543***	−2.698*	−0.283	1.139	−0.246
31	G-DLR	MPshock	5.693***	11.054***	−10.604***	0.901	0.855	−2.191
32	DLR	MPshock	2.156**	3.099***	−2.214*	1.156	1.655*	−0.102
33	G-DLR	EPU&GPR	6.425***	9.104***	−11.179***	1.251	4.629**	−0.876
34	DLR	EPU&GPR	2.306***	2.835***	−2.578**	0.717	2.490***	0.215
35	G-DLR	5year FE	9.813***	10.310***	−11.859***	0.090	2.327	−3.912*
36	DLR	5year FE	2.911***	3.128***	−2.726**	0.685	2.273**	−0.412
37	G-DLR	20year FE	6.578***	11.904***	−7.859**	−2.151	0.743	−0.538
38	DLR	20year FE	2.564**	4.180***	−2.000	0.193	1.859*	0.042
39	G-DLR	DriscollKraay	7.027***	11.562***	−9.369***	−3.196	−0.589	−1.279
40	DLR	DriscollKraay	2.608***	3.873***	−2.540	−0.221	1.432	−0.183

(*Continued*)

With its reserve currency, the world's largest economy, and financial markets, the United States' financial risk could affect 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 of the changes in local growth. Thus, we conclude that the United States plays a pivotal role in global financial cycles.

In Rows 41 through 48, we show that during the postwar and post–Bretton Woods eras, both local and global risk cycles matter when explaining economic growth, while the impact of global risk is significantly higher. The

Table 5
(Continued)

	Shock	Robustness	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
41	G-DLR	postWWII	6.960***	11.696***	−9.759***	−3.896	−0.508	−1.723
42	DLR	postWWII	2.466**	3.865***	−2.522*	−0.327	1.303	−0.254
43	G-DLR	postBW	7.125***	11.298***	−10.509***	−2.701	0.294	−2.141
44	DLR	postBW	2.727***	3.846***	−2.568	0.320	1.637*	−0.266
45	G-DLR	Emerging	0.724***	1.195***	−1.023***	−0.319	0.076	−0.423***
46	DLR	Emerging	0.483***	0.706***	−0.695***	−0.110	0.133	−0.084
47	G-DLR	Developed	0.542***	0.767***	−0.750***	−0.005	0.122	−0.011
48	DLR	Developed	0.226*	0.415**	−0.292	0.112	0.153	−0.090

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 1,000 and 10,000 instead of 5,000. In addition, we estimate the low-volatility state if the current country's volatility is below the one-standard-deviation band. 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 (10) 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 the credit spreads (Credit spr), change in exchange rates (ΔXR), the monetary policy surprise series from Romer and Romer (2004) (MPshock), the economic policy uncertainty index of Baker, Bloom, and Davis (2016), and the geopolitical risk index of Caldara and Iacoviello (2022) in the control set. Sixth, we use 5-year and 20-year 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 and 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. * $p<.1$; ** $p<0.05$; *** $p<0.01$.

results are qualitatively similar over the whole sample period, supporting our findings. Finally, we find that the impact of G-DLR over 3 years is stronger for emerging 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 than developed countries on international capital markets. 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.

4. Conclusion

The financial sector plays a pivotal role in the macroeconomy, as has become increasingly apparent with 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 about the state of the risk cycle. While the posterior is not directly observable, we proxy it by the duration of low risk. 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 the 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 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, in aggregate, low-risk perceptions are followed by higher growth, with two exceptions: 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 the case, with an overall negative impact on growth.

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 through 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, policy makers, justifiably intent on preventing another crisis, 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 as well. The aggregate impact of a low-for-long volatility environment on growth depends on the prevailing level of financial vulnerabilities. When such vulnerabilities increase, for example in the form of excess nonfinancial sector credit, the economy is expected to be more fragile and less resilient to adverse shocks. Our results point to the importance of policy makers 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 used 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 task of enhancing the efficiency of the global financial and economic systems is 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 Coverage

Table A1

Country	Classification	Coverage	Market index
Argentina	Emerging	Jan. 1956–June 1958/ Dec. 1966–Dec. 2016	Argentina Swan, Culbertson and Fritz/ 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/ Dec. 1992–Dec. 2016	Egyptian SE/ 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/ May 2002–Dec. 2016	Hungary Stock Market/ OETEB Hungary Traded
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)

(*Continued*)

Table A1
(Continued)

Country	Classification	Coverage	Market index
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
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)

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 United States, between 1900 to 1923, the Cowles Commission's back-calculated composite of stocks is used. After 1923, S&P is used. See Global Financial Data for details. *Source*: Global Financial Data.

Appendix B. Data Definitions and Sources

- $\text{DLR}_{i,t}$: Duration of low risk, calculated as in (10). 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 analogously 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 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.
- ΔSTIR: Change in short-term interest rates. Three-month Treasury Bill yields, from GFD from 1900.
- ΔXR: Change in exchange rates, local currency with respect to U.S. dollar. Data from 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, Engstrom, and Xu's (2021) risk aversion measure.
- PVS: Pflueger, Siriwardane, and Sunderam's (2020) PVS.
- Positive macro surprises: The average of the Scotti (2016) macroeconomic surprise index, provided that the index is positive.
- BEX uncertainty: Bekaert, Engstrom, and Xu's (2021) uncertainty index.
- Liquidity shocks: The negative difference between stock market turnover 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 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. Connection of θ with the Model Parameters

Rewrite the posterior (7) using (8):

$$\alpha_{t|t} = \frac{\phi_L\left((2q-1)\alpha_{t-1|t-1}+(1-q)\right)}{(\phi_L-\phi_H)(2q-1)\alpha_{t-1|t-1}+(1-q)\phi_L+q\phi_H}, \tag{C1}$$

$$= \frac{A\alpha_{t-1|t-1}+B}{C\alpha_{t-1|t-1}+D}, \tag{C2}$$

where

$$A = \phi_L(2q-1) \tag{C3}$$

$$B = \phi_L(1-q) \tag{C4}$$

$$C = (\phi_L-\phi_H)(2q-1) \tag{C5}$$

$$D = (1-q)\phi_L+q\phi_H \tag{C6}$$

$$\phi_L = \phi\left(\frac{\gamma_1 s_t}{\zeta}\right) \tag{C7}$$

$$\phi_H = \phi\left(\frac{\gamma_1(s_t-1)}{\zeta}\right). \tag{C8}$$

We apply a first-order Taylor approximation to (C2):

$$\alpha_{t|t} \approx \alpha_{t|t}\bigg|_{\alpha_{t-1|t-1}=0} + \alpha'_{t|t}\bigg|_{\alpha_{t-1|t-1}=0} \alpha_{t-1|t-1} \tag{C9}$$

$$\approx \frac{B}{D}+\left(\frac{A}{D}-\frac{CB}{D^2}\right)\alpha_{t-1|t-1}. \tag{C10}$$

From (C10) and (10), it follows that θ can be approximated as:

$$\theta \approx \frac{A}{D}-\frac{CB}{D^2}, \tag{C11}$$

and plugging (C3) – (C8) into (C11), we reach the approximation for θ:

$$\theta \approx \frac{(2q-1)\phi_L}{(1-q)\phi_L+q\phi_H}-\frac{(1-q)\phi_L(2q-1)(\phi_L-\phi_H)}{((1-q)\phi_L+q\phi_H)^2}. \tag{C12}$$

Note that, by definition, $0<B/D<1$. In order for the posterior to be bounded by 0 and 1, then $B/D<1-\theta$.

Appendix D. The Effects of Local DLR on Investment, Capital Flows, and Lending Standards

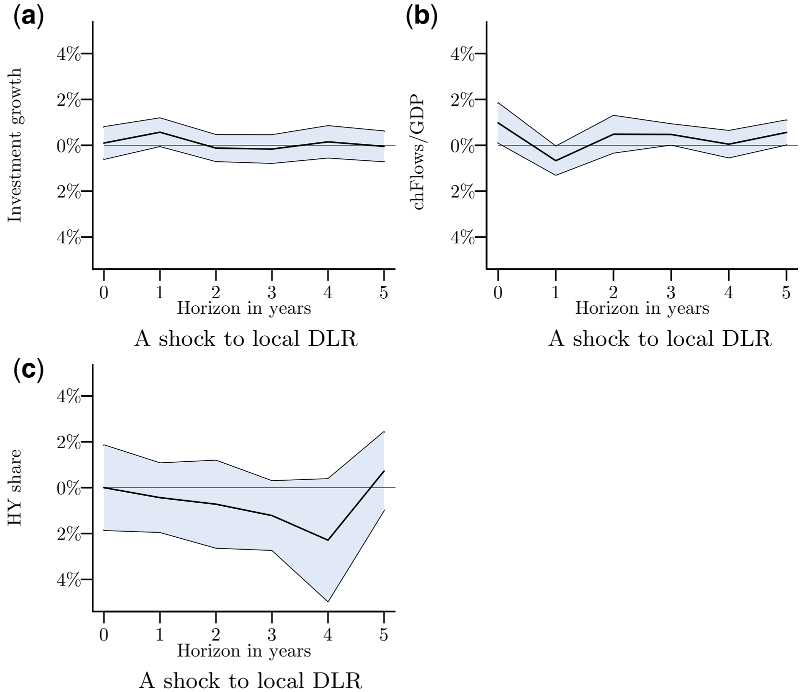

Figure D1
Impact of the perception of low risk on investment, capital flows, and lending standards
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with their associated 95% confidence band of investment growth, changes in portfolio inflows, and lending standards to a shock to the local duration of low volatility (DLR), which is introduced in Section 1.2. 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 (14) 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.

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