THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

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Jon Danielsson
Marcela Valenzuela
Ilknur Zer

SRC Discussion Paper No 100
June 2020

Systemic Risk Centre

Discussion Paper Series

ISSN 2054-538X

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JEL Classification: E32, E44, G15

Keywords: Financial volatility, economic growth, credit booms

This paper is published as part of the Systemic Risk Centre's Discussion Paper Series. The support of the Economic and Social Research Council (ESRC) in funding the SRC is gratefully acknowledged [grant number ES/R009724/1].

Jon Danielsson, Department of Finance and Systemic Risk Centre, London School of Economics

Marcela Valenzuela, School of Management, Pontificia Universidad Católica de Chile and Systemic Risk Centre, London School of Economics

Ilknur Zer, Federal Reserve Board and Systemic Risk Centre, London School of Economics

Published by
Systemic Risk Centre
The London School of Economics and Political Science
Houghton Street
London WC2A 2AE

Financial Risk and Economic Growth, 1870–2016*

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Abstract

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Keywords: Stock market volatility, uncertainty, Minsky's hypothesis, financial instability, risk-taking, granular instruments (GIV), global financial cycles
JEL classification: F30, F44, G15, G18, N10, N20

*Jon Danielsson is at the London School of Economics (LSE) and the director of the Systemic Risk Centre at LSE. Marcela Valenzuela is at the School of Management, Pontificia Universidad Católica de Chile. Ilknur Zer is at the Federal Reserve Board. We thank Nelson Camanho, Alessandro Rebucci, Andreas Uthemann and Jean-Pierre Zigrand, as well as seminar participants in the Nova School of Business and Economics, Banco de Portugal, Banque de France, Federal Reserve Board, International Monetary Fund (IMF) Macro-Financial Research Division, University of Cyprus, Pontificia Universidad Católica de Chile, and Adolfo Ibáñez University for valuable comments. Alessandro De Trane provided excellent research assistance. Philipp Adämmer wrote the LPIRFS R package we used in the analysis. The webappendix for the paper is `modelsandrisk.org/appendix/volatility-growth`. Danielsson thanks the Economic and Social Research Council (United Kingdom) [grant number: ES/K002309/1] for its support. Valenzuela acknowledges the support of Fondecyt Project No. 1190477 and Instituto Milenio ICM IS130002. The views in this paper are solely those of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

1 Introduction

The Global Financial Crisis reminded us of the importance of the financial sector for the macroeconomy, a lesson many had forgotten in the decades after the previous global crisis, the Great Depression. Financial risk matters. It is necessary for investment and growth but also drives uncertainty, inefficiency, recessions, and crises. While the interplay between finance and macroeconomics is complex, our interest is on one particular dimension: how economic agents' perception of financial risk affects growth.

A high-risk environment is characterized by high uncertainty and, hence, is detrimental to economic growth because it increases the real option value of waiting on investment, encouraging firms to delay their investments (Dixit and Pindyck, 1994; Bloom, 2009; Bloom et al., 2018). High risk also exacerbates information asymmetry problems, either increasing the cost of credit to households and firms or reducing the ability to intermediate funds, with both weakening aggregate economic activity (Gilchrist et al., 2014; Ferreira, 2016).

If high risk is detrimental to growth, one might expect low risk to be similarly beneficial for growth. We hypothesize that it is, but only in the short run. As time passes, a reversal in the impact of low risk on growth becomes increasingly likely—what we term a boom-to-bust cycle.

At the start of the cycle, when agents first observe risk is low, they respond by increasing the amount of risky investments they make. However, because risk is a latent variable and can be measured only with uncertainty, the strength of their belief that risk is actually low affects their desire to invest. As they observe repeated periods of low risk, their posterior probability of the accuracy of the low-risk signal increases, similar to the Bayesian learning models of Morris (1996) and Veronesi (1999).

Hence, as periods of low risk become longer, agents' risk appetite increases: investors require less compensation for risk, and lenders are encouraged to lend more than they would do otherwise, as in Fostel and Geanakoplos (2014). The consequent increased investments have a positive impact on growth. However, as time passes, the agents eventually run out of higher-quality investments, as in Greenwood and Hanson (2013), laying the seeds for a reversal—when the boom cycle turns to bust.

Thus, a stable (low risk) environment endogenously induces economic agents to increase their risk-taking progressively, leading to an eventual instability—the root of Minsky's (1977) famous dictum "stability is destabilizing." Such a chain of events is consistent with Schularick and Taylor's (2012) and Aikman et al.'s (2017) notion of excessive credit growth leading to a fragile economy, one that is less resilient to adverse shocks.

Both local (domestic) and global low risk affect the agents' risk appetite, as emphasized in the recent literature on the nexus among risk, asset prices, and global cycles. We expect the global risk environment to be a powerful determinant of local growth for several reasons, including free capital flows, synchronized monetary policies across the world economies, financial institutions' search for higher yield through international investments (IMF, 2019), and the presence of a globalized banking system (Bruno and Shin, 2015). Such global factors are likely to be particularly important for growth after the collapse of the Bretton Woods system as capital markets have progressively opened up. Jordà et al. (2018) find that global risk appetite strongly affects global cycles through international risk-taking, especially over the past three decades. In that environment, the impact of the United States and its reserve currency might be particularly strong, as shown by Rey (2018), where U.S. market volatility and monetary policy decisions drive global financial cycles.

These theoretical insights guide us toward two empirical hypotheses not considered before in the literature. First, the impact of a persistent low-risk environment on growth should start positive but then, as time passes, become increasingly detrimental as the overall riskiness of investments increases and investors run out of attractive low-risk alternatives. The empirical consequence is a testable boom-to-bust cycle for long-lasting low risk.

Second, by comparing the persistence of local low risk (for a country) with global low risk (persistence of low risk aggregated across the world), we expect global persistent low risk to be at least as important as its local counterpart in contributing to the boom-to-bust cycle. Risk appetite of global investors and asset allocations affect capital flows and domestic investment, particularly for countries dependent on such inflows for investment financing, and, hence, growth.

Our main empirical device is the duration of low volatility (DLV). Two related factors contribute to DLV: measured volatility being low and, even more important, the length of that volatility environment. More specifically, DLV takes low (realized) volatility—volatility below its long-run historical trend—as a starting point, further counting the number of years in which volatility is below the trend. We define the duration of high volatility (DHV) analogously. A key advantage is that our duration measures can easily be calculated with publicly available data over long periods and many countries. While DLV and DHV are constructed locally—that is, for each country separately—we further obtain a global version of the duration measures by calculating a gross domestic product- (GDP) weighted average of them.

DLV then captures the agent's belief that an observation of low risk is accurate—that is, associated with the posterior probability that market risk is low. When volatility stays low, DLV increases, as does the agent's risk appetite, stimulating demand for risky assets, and, by using both local and global DLV, we can separate the importance of the domestic risk environment from the international one.

When we construct the duration measures, we separate volatility in a particular year into either high or low volatility using the trend of volatility. It is necessary to use the trend, rather than the mean or some other constant separator for the decomposition, as the impact of volatility depends on the prevailing level of volatility in a particular country and time. A particular measurement of volatility might be seen as worryingly high in one case and as comfortably low in another, so it is necessary to find the appropriate trend for each country and time. To estimate the trend, similar to our earlier work (Danielsson, Valenzuela, and Zer, 2018), we use a one-sided Hodrick-Prescott (1997) filter.[1] A one-sided filter uses only past information to estimate the trend for a given time, which is necessary in our case because we run predictive regressions.

Instead of counting the consecutive number of years in each high- and low-volatility state, an alternative way to calculate DLV and DHV is to measure the magnitude of low or high volatility cumulatively, provided they stay in their respective states. Empirically, both approaches yield similar results, but DLV and DHV are preferred for three reasons. First, they are unit free, so we do not have to worry about how the different magnitudes of volatility across countries and time may affect the results. Second, they are easily interpreted, as we can quantify the impact of an additional year of low or high volatility. Finally, if we were to use the cumulative of low volatility, a single observation of very low volatility could be observationally equivalent to high persistence of low risk but would likely have different economic effects.

When studying the effects of risk on growth, we can take two empirical paths: either use recent data, with the advantage of an abundance of variables from which to choose, or aim for the largest sample in the cross section and time dimension. We opt for the second approach, as it allows us to capture many business and financial cycles in countries in various states of financial and economic development. We have data for 74 countries, from 1870 to 2016, where available—on average, 56 years per country.

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

First, a positive shock to DHV—that is, a one-year increase in the persistence of the high-volatility environment—has an unambiguous negative impact on economic growth, contemporaneously and in the next year. A one-year increase in local DHV decreases economic growth 0.24% cumulatively, whereas the economic impact of

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

global DHV is four times higher at 0.97%. These results are in line with the extant literature, which associates high volatility with high uncertainty, harming growth.

Second, a positive shock to DLV—that is, the low-risk environment lengthening by one year—has a boom-to-bust impact on economic growth. Growth increases contemporaneously and especially one year hence, with a significant reversal in year two. We term this finding as a boom-to-bust, or $++-$, cycle. The impact of global DLV is more than twice that of the local counterpart. Cumulatively, the impact of both is positive, suggesting that a more prolonged low-risk environment has a permanent positive impact on GDP growth. Even with a correction in year two, a one-year increase in local DLV increases economic growth 0.13% across the three-year ++– cycle, while a one-year rise in global DLV leads to a 0.62% increase in growth.

While we find a significant impact of DLV on future growth, the result may likely suffer from endogeneity. An omitted variable can affect both stock market volatility and growth, or the causality can go from growth to volatility but not in the opposite direction. To alleviate such concerns, we use Gabaix and Koijen's (2019) granular instrumental variable (GIV) approach. The underlying idea is that a few large countries drive the aggregate outcomes, and, hence, their idiosyncratic shocks can be used as instruments for the aggregate ones. Our results hold when we correct for endogeneity by the GIV approach.

Third, we find that the boom-to-bust effect of global low volatility on economic growth becomes stronger over time, with a particularly strong impact for the post-Bretton Woods era, after 1973, underscoring the importance of heightened globalization and global financial cycles over the past decades. Furthermore, when we use U.S. DLV as a proxy for global DLV, we find it affects growth significantly. However, the impact is only half as strong as that of the global DLV that considers all other countries excluding the United States, implying that while the U.S. financial markets are important, their effects on risk appetite are still limited.

Fourth, persistent global low volatility has a particularly strong impact during credit booms. If a country is in the highest decile of credit growth in a particular year, the amplitude of the boom-to-bust cycle is double what it would otherwise be and is longer lasting. In particular, a shock to global DVL translates into a 0.5 contraction on growth over the next three years. We conclude that if a country experiences "excessive" credit growth, its financial system could be in a more vulnerable state, so that increased global risk-taking, fueled by a low-volatility environment, further exacerbates financial vulnerabilities, making the economy more fragile and less resilient to adverse shocks. This result is consistent with Schularick and Taylor's (2012) crisis study, where excessive credit growth leads to crises, and with Danielsson, Valenzuela, and Zer (2018), where low risk can lead to a crisis because it results in higher financial-sector leverage and credit booms.

Fifth, we examine in more detail possible mechanisms for how low risk affects economic growth, focusing on three channels: domestic investment, capital flows, and the deterioration of lending standards. However, as the necessary data are available only in more-recent history, our coverage here is mostly post-1960s. A positive global DLV shock has a significant and high impact on domestic investment and capital flows. Initially, the impact is positive, but turns negative in years two to four. That is, because of their increased appetite for risk, investors seek high-risk alternatives in a low-risk environment, ultimately allocating funds to developing countries, increasing net capital inflows and domestic investment, and, hence, growth, followed by a correction. Moreover, we find a deterioration of lending standards (measured via the high-yield share of bond issuance) following a long-lasting volatility environment. By contrast, the aggregate impact of local DLV on capital flows is smaller than that of global DLV, indicating that the global risk environment, not the local, drives capital flows. Similarly, local DLV has no impact on investment growth and debt-issuer quality.

Finally, by splitting the sample into countries classified by the IMF as developed or emerging, we find that persistent global volatility affects emerging countries much more strongly compared with the developed ones, with a higher aggregate impact and amplitude.

These findings lend support to our hypothesis that the impact of persistent low volatility on growth is quite different from that of high volatility and that the effect of global risk is more important than local, especially when driving the reversal on growth. The impact of persistent high volatility and volatility itself is what one might expect, an immediate fall in investment and growth, but only over the short term. By contrast, persistent low volatility has a longer-term impact—initially positive but eventually followed by a reversal, yet still positive overall. The risk appetite that is induced by the increase in DLV has a positive impact on growth. Thus, it initially encourages risky investments that ultimately augment growth but at the cost of building up of vulnerabilities in the economy.

Taken together, our results contribute on several important policy debates. Consider macroprudential regulations. After the crisis of 2008, policymakers, justifiably intent on preventing a repeat, have been actively aiming to reduce the amount of risk financial institutions can take—*de-risking* the financial system. In other words, they want to reduce their risk by requiring higher levels of capital and imposing stringent lending standards. While such de-risking promises to reduce the likelihood of a costly financial crisis, our findings show that it may reduce economic growth. The aggregate impact of a longer low-volatility environment on growth depends on the prevailing level of financial vulnerabilities. When such vulnerabilities increase, such as 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 policymakers considering the joint impact of macroprudential policies on the likelihood of crises and growth.

Our final policy conclusion focuses on the importance of the global risk environment. While global and local risks both matter, global risk matters more. National policymakers concerned with growth are hence constrained and need to take global financial cycles into account. Global institutions like the IMF, World Trade Organization, and Financial Stability Board tasked with enhancing the efficiency of the global financial and economic system are important. Individual countries cannot ignore the global risk environment, however much they might want to because it contributes more strongly to the risk appetite of domestic agents than does their local risk environment. That consideration is especially important for emerging countries, those without deep domestic financial markets. U.S. financial markets are an important contributor to the global risk environment, yet their effects on other countries' local risk appetite are still limited.

Our paper is related to several branches of the literature. First, the vast literature concerned with the effects of financial volatility on growth, such as Bloom (2009) and Bloom et al. (2018), among others, reach the main conclusion that volatility harms growth via reduced investment and increased asymmetric information, as it increases uncertainty. Second, in the earlier literature, Levine and Zervos (1998), Beck et al. (2000), Beck and Levine (2002), and Levine (2006), among others, stress the pivotal role of the structure of the financial system for economic growth. In contrast, the more recent literature, including Avdjiev et al. (2016), Rey (2018), and Jordà et al. (2018) focuses on the importance of global factors driving economic growth. Third, in the related literature on agents' perception of risk and its effects on the macroeconomy, López-Salido et al. (2017) find that elevated credit sentiment, reflecting how economic agents see financial and economic conditions, harms growth, while Pflueger et al. (2018) identify a positive relationship between risk appetite and investment. Finally, recent literature, such as Schularick and Taylor (2012) and Danielsson, Valenzuela, and Zer (2018), finds evidence of the adverse effects of excessive risk-taking.

We extend this literature in several dimensions. First, we distinguish between the impacts of high- and low- risk environments on growth. We particularly focus on the persistence of the global low-volatility environment and show that its effects on growth are not linear, but rather generate boom periods followed by reversals due to excessive accumulation of financial vulnerabilities. Second, because we use global data, we can separate the impact of local risk from global risk and identify the contribution of the United States to local risk appetite. Furthermore, to capture as many business and financial cycles as possible, we use data that go back almost 150 years, covering 74 countries.

Finally, we find that the persistence of low volatility is associated with agents' risk appetite, as measured by common proxies in the literature. In particular, we calculate the contemporaneous correlation between DLV and the Volatility Index

(VIX), the risk aversion measure (BEX) of Bekaert et al. (2019), and the price of volatility stocks (PVS) of Pflueger et al. (2018). The correlation coefficient between DLV and VIX is -0.48, BEX is -0.35, and PVS is 0.37, all significant at a 1% level, suggesting a strong association between DLV and risk appetite. One advantage of DLV is that it can easily be calculated for a large number of countries and for many years and is available both in local and global forms.

2 Data and empirical approach

2.1 The duration of low and high volatility

Our interest is in examining the impact of financial risk and, in particular, persistent low and high risk on economic growth. We estimate risk by realized stock market volatility and capture the persistence of low and high volatility by the *duration of low volatility* (DLV) and *duration of high volatility* (DHV), respectively. $\text{DLV}_{i,t}$ counts how long the volatility of the stock market remains low for country i in year t. Define an indicator variable $X_{i,t}$ for whether country i is in a low-risk environment in year t (1) or not (0):

$$X_{i,t} = \begin{cases} 1 & \text{if volatility is low} \\ 0 & \text{otherwise.} \end{cases} \qquad i = 1, \ldots, N_t, \tag{1}$$

where N_t is the number of countries with observations in year t. The definition of $\text{DLV}_{i,t}$ is then

$$\text{DLV}_{i,t} = (\text{DLV}_{i,t-1} + X_{i,t})X_{i,t},\ \text{DLV}_{i,0} = 0. \tag{2}$$

DHV is constructed analogously.

We obtain low and high volatility ($\sigma_{i,t}^{\text{low}}$, $\sigma_{i,t}^{\text{high}}$) as volatility ($\sigma_{i,t}$) below and above the prevailing trend, $\hat{\tau}_{i,t}$, following our earlier work (Danielsson, Valenzuela, and Zer, 2018):[2]

$$\begin{aligned} \sigma_{i,t}^{\text{high}} &= \begin{cases} \sigma_t - \hat{\tau}_{i,t} & \text{if} \qquad \sigma_t \geq \hat{\tau}_{i,t} \\ 0 & \text{otherwise,} \end{cases} \\ \sigma_{i,t}^{\text{low}} &= \begin{cases} \sigma_t - \hat{\tau}_{i,t} & \text{if} \qquad \sigma_t < \hat{\tau}_{i,t} \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{3}$$

We calculate annual realized volatility as the standard deviation of monthly market returns over a year, scaled by the consumer price index (CPI). The alternative

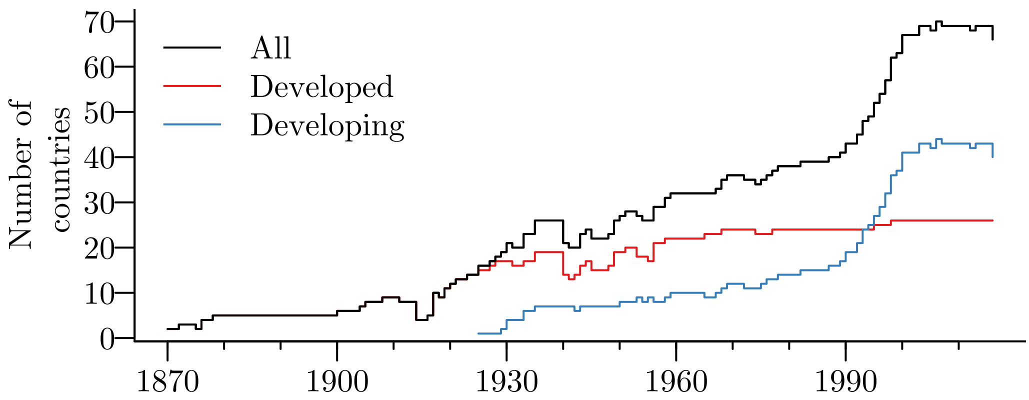
[2]Alternatively, we could model the trend levels of volatility via Markov switching models, along the lines of Hamilton and Susmel (1994). However, given our sample size, with Markov switching models we are limited to at most two regimes. In addition, the distinction between the regimes is sharp—that is, we jump from one to the other. Our data indicates that there are more than two regimes and the transition from one to the other is relatively smooth.

would be to use a conditional volatility model from the generalized autoregressive conditional heteroskedasticity (GARCH) family.[3] We do not think such models are suitable for the annual volatility we require. Not only is the half life of shocks to GARCH volatility typically less than one year, but such models also require hundreds of observations for estimation, a luxury we do not have.[4]

We collect monthly stock market indexes from the Global Financial Data (GFD), with data available for 74 countries, from 1870 to 2016. At the beginning of the sample, we have observations on only four countries, the United States, Great Britain, Germany, and France. Over time, as shown in Figure 1, the number of countries increases steadily (Table A1 in Appendix A lists individual countries' coverage). There is a sharp uptick in the number of countries with stock markets following World War I. The largest increase in the sample size comes from newly independent developing countries establishing stock markets, identified as the blue line in Figure 1.

Figure 1: Data coverage

Number of countries with available stock market return data from 1870 to 2016. The classification into developed and developing is from the International Monetary Fund, from 2016.



We estimate the trend of volatility, $\hat{\tau}_{i,t}(\lambda)$, with a smoothing factor λ using a

[3]This group includes Engle's (1982) autoregressive conditional heteroscedasticity (ARCH) process, Bollerslev's (1986, 1987) GARCH model, or any of the more recent extensions.

[4]While conceptually we could have used the approach of Pakel et al. (2020) and employed composite maximum likelihood estimation, it depends on a balanced panel and on assuming the GARCH dynamic parameters are constant across countries, an assumption we are unwilling to make.

one-sided Hodrick and Prescott (1997) (HP) filter:[5]

$$\hat{\tau}_{i,t}(\lambda) = \min_{\{\tau_{i,t}(\lambda)\}_{t=1}^{T_i}} \sum_{t=1}^{T_i} \left[\sigma_{i,t} - \tau_{i,t}(\lambda)\right]^2 + \lambda \sum_{t=2}^{T_i-1} \left\{\left[\tau_{i,t+1}(\lambda) - \tau_{i,t}(\lambda)\right] - \left[\tau_{i,t}(\lambda) - \tau_{i,t-1}(\lambda)\right]\right\}^2, \quad i = 1, \ldots, N, \quad (4)$$

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. We set $\lambda = 5000$.[6]

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

2.2 Global low and high volatility

DLV and DHV measure the persistence of low and high volatility, respectively, in a particular country. We expect the global risk environment to contribute strongly to the risk appetite of domestic agents, and, hence, affect growth, more than their local risk environment. After all, global financial markets are a vital source of funds for investment in many countries and for investors seeking global diversification.

We use local DLV as an input into the calculation of global DLV (G-DLV$_t$), which is obtained as the GDP-weighted average of the local measure (DLV$_{i,t}$) across all countries with data in year t. G-DHV$_t$ is calculated similarly.[7] The G-DLV measure in Figure 3 further marks key stress events in world economic history.

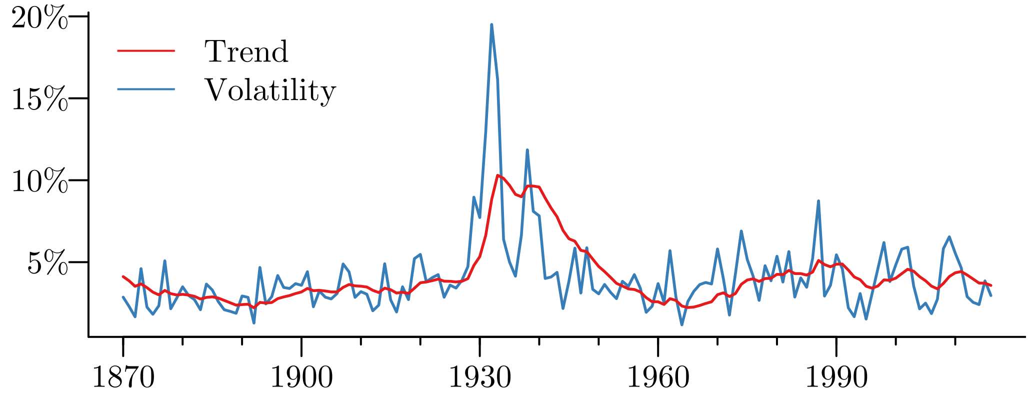
[5]As our analysis builds on predictive regressions, we use only past information when constructing the explanatory variables. Hence, we employ a one-sided HP filter, constructed by running the HP filter recursively through time by using only data available up to year t to estimate the trend for year t. 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.

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

[7]As the number of countries varies over time, the global risk is constructed from an unbalanced

Figure 2: United States volatility and trend

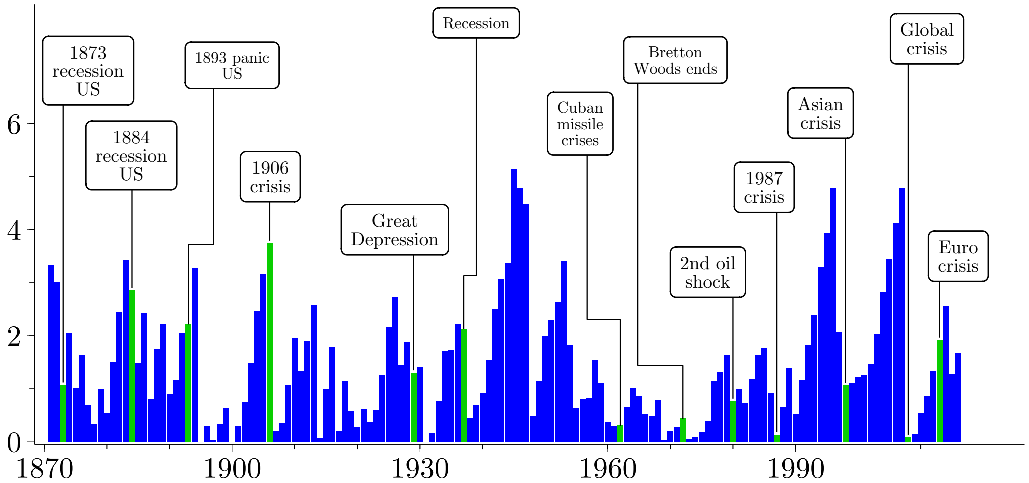
Annual volatility and estimated trend for the United States. Volatility is calculated as the standard deviation of the previous 12 monthly real returns. The trend is calculated by a one-sided Hodrick-Prescott filter with a smoothing parameter $\lambda = 5000$.



Visual inspection indicates that high G-DLV 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 1870 sample,

Figure 3: Global duration of low volatility

The global duration of low volatility (G-DLV) is calculated as the gross domestic product-weighted average of the local measure ($\text{DLV}_{i,t}$). $\text{DLV}_{i,t}$ is the consecutive number of years, where a country experiences a low-volatility environment, as described in Section 2.1. Relevant economic events are also marked in the figure.



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

panel. Hence, we check the robustness of our findings when global risk is obtained from a balanced panel considering current G7 constituents (United States, United Kingdom, France, Germany, Italy, Canada, and Japan). The main findings are robust, and results are provided in Section 4.

in the sample were also occupied and markets were disrupted in various ways, with arbitrary closures and confiscation, currency reforms, or very high inflation. We, therefore, drop the World War II years (1939–45) from the regressions.

2.3 Other variables used in the analysis

The dependent variable in our analysis is the log-GDP growth rate of each country in the sample. Annual GDP per capita and population numbers are from the Maddison (2003) database, available at `http://www.ggdc.net/maddison/` from 1870, used by several authors, including Acemoglu et al. (2008) and Reinhart and Rogoff (2009).

Besides controlling for lagged growth, we use other control variables identified in the literature as having an effect on economic growth. In the baseline specification, we include inflation, institutional characteristics of a country, and log GDP, as they are available from 1870. The first is motivated by several studies that find inflation has an impact on economic growth (see, for example, Barro, 1995). Inflation is calculated as the annual percentage change in the CPI, obtained from the GFD.

Moreover, Cerra and Saxena (2008) find that institutional characteristics and governance of a country can affect political and macroeconomic stability. The variable we use is POLCOMP 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.

Levine and Zervos (1998), Beck et al. (2000), Beck and Levine (2002), and Levine (2006) stress the pivotal role of the structure of the financial system for economic growth. Developed financial systems and institutional quality are beneficial for the efficient allocation of investment in the economy, hence stimulating growth. While many financial development indicators have been proposed in the literature, such as stock market capitalization and banking-sector depth measures, we include per capita income as a proxy for an aggregate financial development indicator (see, for example, Levine, 2006, for a survey).

Other control variables include changes in short-term interest rates and exchange rates. We obtain both variables from the GFD. However, coverage is limited. Hence, we keep them in the robustness section. Appendix B lists all variables used in the analysis, along with their definitions and data sources.

2.4 Econometric set-up

Our main empirical device is impulse responses obtained from Jordá's (2005) local projection method. Specifically, we use a panel setting to regress the dependent variable, y, $t+h$ 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:

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

where the shock variable is $S_{i,t}$ and the impulse response is hence β^h. $X_{i,t}$ is the vector of control variables described in Section 2.3 (log GDP, inflation, institutional quality), as well as DLV and DHV and their global counterparts. Finally, α_i^h are country fixed effects, and η_t^h are decade fixed effects.[8] We set the number of lags at five, $L = 5$.

3 Empirical results

Our main empirical interest is in investigating how the persistence of risk environments, both local and global, affects the risk appetite of agents and ultimately economic growth. The specific empirical device we use is the duration of low volatility (DLV) and its high-volatility counterpart, the duration of high volatility (DHV).

3.1 Duration of high and low volatility and growth

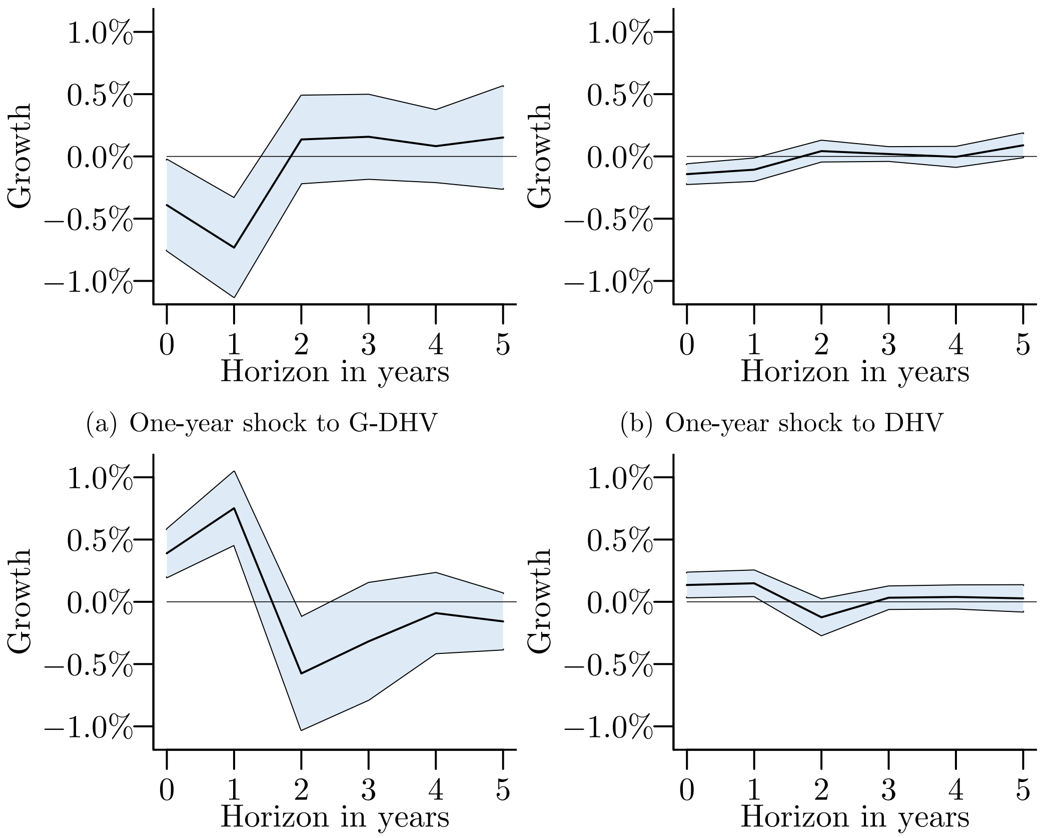
We measure the impact of shocks to the persistence of a volatility regime on growth, by using the panel impulse response regressions (5), identifying the impact contemporaneously ($h = 0$) and up to five years into the future ($h = 5$). The full sample contains observations from 74 countries, from 1870 until 2016, with 4,303 observations in all. We control for the inflation rate, the degree of institutionalization of political competition, and log-GDP per capita.

Panels (a) and (b) of Figure 4 show the impact of DHV on growth. A positive shock to DHV—that is, a one-year increase in the persistence of high volatility—has an unambiguous negative impact on economic growth, contemporaneously and in the next year. The effect of global DHV (G-DHV) on growth is much stronger than local. A one-year increase in local DHV decreases economic growth 0.24%

[8] To control for the financial and economic development throughout time, we include 10-year fixed effects. 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.

Figure 4: The impact of duration of high and low volatility on growth

This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to duration of high volatility (DHV) and duration of low volatility (DLV). In Panel (a), we present the results for a shock in global DHV—that is, when the world remains in a high-volatility environment for an additional year. Panel (b) shows the results for local DHV. In Panel (c), we present the results for a shock in global DLV (G-DLV)–that is, when the world remains in a low-volatility environment for an additional year. Finally, in Panel (d), we show the results for local low volatility. Global and local measures are introduced in Section 2.1. In all of the cases, we run regressions (5) with log-GDP growth as the dependent variable. All regressions include inflation rate, the degree of institutionalization of political competition, log-GDP per capita, lagged DLV and lagged DHV and their global counterparts, and country and decade fixed effects. We dually clustered standard errors at the country and year levels. Data spans 1870 to 2016 for 74 countries.



(a) One-year shock to G-DHV

(b) One-year shock to DHV

(c) One-year shock to G-DLV

(d) One-year shock to DLV

over $h = 0$ and $h = 1$, whereas the economic impact of G-DHV is four times greater than its local counterpart, with a cumulative contraction of 0.97%.

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

We then test our two empirical hypotheses. The first is that the impact of an increase in DLV is initially positive for economic growth and then turns negative as time passes—a boom-to-bust cycle. The second is whether the impact of global DLV (G-DLV) is as strong as that of local DLV in its impact on growth.

The impact of DLV is positive contemporaneously and the following year, turning negative two years afterwards, as reported in Panels (c) and (d). G-DLV has a much stronger economic impact than does its local counterpart, and the amplitude of its boom-to-bust cycle is higher, as well as its cumulative impact. If the world remains in a low-volatility environment an additional year, cumulatively, the GDP growth of a typical country will increase 0.62% over the boom-to-bust cycle, while a one-year increase in local low volatility leads only to a 0.13% increase in its growth.

The empirical results give a conclusive answer to our initial hypothesis. The impact of persistent low risk is much different from that of persistent high risk. It is both larger in magnitude and longer lasting—a boom-to-bust cycle compared with a bust only. As the persistence of low risk increases, so does the risk appetite of economic agents, initially leading to higher growth, but ultimately resulting in a reversal amid accumulated financial vulnerabilities.

Furthermore, the global risk environment is much more important than the local environment in its contribution to risk appetite and, hence, growth. Both conclusions raise questions about the specific mechanisms that lead to the boom-to-bust cycle, underscoring the importance of the persistence of global low volatility, and whether particular countries or periods in history are especially affected. Thus, for the rest of the empirical analysis, we address those questions, focusing on the persistence of global low volatility.

3.2 Duration of low risk and growth: A granular instrumental variable approach

In our estimation methodology, we focus on the lead-lag relationship between the persistence of a volatility regime and growth. Furthermore, our main variable of interest, G-DLV, is estimated by using the countries' stock return volatilities and, hence, is less likely to be affected by local economic growth. Consequently, our findings may suffer from an endogeneity problem. Omitted variables may affect both G-DLV and growth simultaneously, or the causality may still run from the economic growth to stock returns.

To alleviate such concerns and investigate the causal effect of G-DLV on economic growth, we employ the granular instrumental variable (GIV) approach proposed by Gabaix and Koijen (2019). The underlying idea is that a few large countries drive aggregate outcomes, and their idiosyncratic shocks affect the aggregate ones. Hence, those idiosyncratic country-level shocks can serve as valid instruments for the aggregate ones.

Following Gabaix and Koijen (2019), we construct an instrument for G-DLV$_t$, by extracting the idiosyncratic component of GDP growth by large countries in terms of their GDP. Let GIV_t denote the instrument for G-DLV$_t$:

$$GIV_t = \sum_{i=1}^{N} w_{it} y_{it} - \frac{1}{N} \sum_{i=1}^{N} y_{it}, \tag{6}$$

where y_{it} is the GDP growth rate for country i in year t and w_{it} are the weights, calculated as the total GDP of country i over the sum of total GDP of all countries in year t.

We run the following first-stage regressions:

$$\text{G-DLV}_t = \beta GIV_t + \sum_{k=1}^{L} \delta_k y_{i,t-k} + \sum_{k=1}^{L} \phi_k X_{i,t-k} + \alpha_i + \eta_t + \varepsilon_{i,t}, \tag{7}$$

G-DLV$_t$ is the global duration of low volatility introduced in Section 2.1; $X_{i,t}$ is the vector of control variables described in Section 2.3 (log GDP, inflation, institutional quality), as well as the DLV and DHV and their global counterparts; α_i^h are country fixed effects; and η_t^h are decade fixed effects. We obtain the predicted global duration of low risk as $\widehat{\text{G-DLV}}_t = \widehat{\beta} GIV_t$.

Finally, the second-stage regressions are as follows:

$$y_{i,t+h} = \beta^h \widehat{\text{G-DLV}}_t + \textstyle\sum_{k=1}^{L} \delta_k^h y_{i,t-k} + \sum_{k=1}^{L} \phi_k^h X_{i,t-k} + \alpha_i^h + \eta_t^h + \varepsilon_{i,t+h}, \tag{8}$$

for $h = 0, \ldots, 5$.

We present the regression results in Table 1. The first-stage results show a positive and significant coefficient, which indicates the strong correlation between G-DLV and the gravity instrument. In the second-stage results, we show that the predicted G-DLV has a significant relation to GDP growth, confirming our main finding: Low periods of volatility have a boom-to-bust effect on economic growth. Indeed, when we correct for endogeneity, we see the impact of G-DLV on growth lasts longer and, in particular, continues to be significant in year three.

3.3 Global low risk and growth in the post-Bretton Woods era

The results discussed earlier focus on the entire sample, but the post-Bretton Woods era (after 1972) is of particular interest. Because, during this time of increasingly heightened globalization, 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 preeminent and even increasing. Hence, we expect the impact of the persistence of global low risk on economic growth to be particularly strong after 1972.

We present the post-Bretton Woods results in Table 2. We find that the full sample results in Figure 4 continue to hold but are amplified. Both the magnitude and the amplitude of the global boom-to-bust cycle increase, and the aggregate impact over the two-year cycle is 13% higher than that of the full sample results. However, the aggregate impact of the local DLV fell 7%. That means the impact of G-DLV is about four times higher than that of local DLV. This result is consistent with the co-movement of financial markets, especially in the stock markets, increasing sharply in the past three decades, reaching historical highs (Jordà et al., 2018).

Several authors have highlighted the pivotal importance of the United States for global financial cycles (Rey, 2018; Jordà et al., 2018; Avdjiev et al., 2016). In the end, with its reserve currency, the world's largest economy, and financial markets, financial risk in the United States could be particularly important for global risk, driving international risk-taking and, thus, affecting growth throughout the world. Our data provide us with an excellent opportunity to explore in more detail the role of the United States in driving the global risk environment. Because G-DLV is the GDP-weighted average of local DLVs, it allows us to specifically identify the contribution of the United States. We do so by creating two alternative versions of G-DLV, the first where U.S. DLV alone is a proxy for G-DLV, and the second where we create G-DLV using data for all countries excluding the United States. We find that, when U.S. DLV is the proxy for G-DLV, the boom-to-bust cycle remains, and it is longer lasting but with a smaller amplitude compared to G-DLV estimates for post-Bretton Woods. Whereas, DLV without the United States (G-DLV$_{\text{-U.S.}}$) has a stronger impact than G-DLV for the same period, both in magnitude and amplitude. Thus, we conclude that while the United States is important, it is not the sole driver of global financial cycles and its effects can still be limited (Table 2).

Finally, we identify developed and emerging (or developing) countries classified by the IMF during the post-Bretton Woods era. We find that, on aggregate over the two year cycle, the persistence of low risk affects emerging countries more strongly than developed countries, with a higher amplitude of the boom-to-bust cycle. Thus, for emerging countries, the persistence of global risk is particularly important, highlighting the pivotal role of global capital markets intermediating funds to such countries. In the end, limits to bank lending in emerging countries may make them more dependent on international capital markets than developed countries. The risk appetite both for international investors who provide capital and for domestic investors who undertake capital projects increases when global risk is perceived as low and falling.

3.4 Conditioning on the credit cycle

The importance of credit and financial conditions on the dynamics of macroeconomic performance has been highlighted by many authors (for example Schularick and Taylor, 2012; Aikman et al., 2017). When financial vulnerabilities increase, such as in the form of excess nonfinancial-sector credit, the economy is expected to be more fragile and less resilient to adverse shocks. In that case, a positive shock to the persistence of a low-volatility environment could actually have a significant adverse effect rather than the aggregate positive effect we found in the baseline specification.

To explore that conjecture further, we define an indicator variable $I^q_{i,t}$ for whether a particular country is above or below a quantile (q) of credit growth in a given year, compared with other countries with observations in the same year.

$$I^q_{i,t} := \begin{cases} 1 & \text{if credit growth}_{i,t} \geq \text{credit growth}^q_t \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

where credit growth^q_t is the q^{th}_t quantile in year t. We measure credit growth as the log first difference of credit to nonfinancial institutions, with data obtained from the Bank for International Settlements, available from 1953 or later, for 40 countries.

We then modify the impulse Panel regressions in (5) to allow for two states, when credit is above or below the quantile:

$$\begin{aligned} \Delta \log \text{GDP}_{i,t+h} = & \quad I^q_{i,t} \left(\beta^{h,\text{high}} S_{i,t} + \Gamma^{h,\text{high}} X_{i,t}\right) \\ & +(1 - I^q_{i,t}) \left(\beta^{h,\text{low}} S_{i,t} + \Gamma^{h,\text{low}} X_{i,t}\right) + \alpha^h_i + \eta^h_t + \varepsilon_{i,t+h}, \\ h = & \quad 0, \ldots, 5, \\ S_{i,t} = & \quad \text{G-DLV}_t. \end{aligned} \tag{10}$$

where $X_{i,t}$ includes lagged GDP growth rate, inflation, log-GDP, and political competition of the country, and lagged DLV and lagged DHV and their global counterparts, similar to the baseline specification. In addition, we control for changes in local interest rates, as they can be important determinants of credit. α^h_i are country fixed effects, and η^h_t are decade fixed effects. $\beta^{h,\text{low}}$ and $\beta^{h,\text{high}}$ are the impulse responses of growth to a shock of G-DLV conditioning on credit growth below and above the quantile threshold (credit growth^q_t), respectively. In what follows, we refer to results from $\beta^{h,\text{low}}$ and $\beta^{h,\text{high}}$ as low and high, respectively.

Figure 5: Impact of the persistence of global low volatility on growth, conditional on the state of the credit cycle.

This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of gross domestic product (GDP) growth rate to a shock to the persistence of global duration of low volatility (G-DLV) conditioning on excessive credit growth. The global volatility measure is introduced in Section 2.1. High credit growth is obtained from equation (9) 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 (10) and plot $\beta^{h,\text{high}}$ based on different quantiles to define excessive credit growth (0.5 and 0.9). For comparison, unconditional impulse responses for the period where we have available credit data are also plotted. All regressions include inflation rate, the degree of institutionalization of political competition, log-GDP per capita, GDP growth, change in short-term interest rates, lagged DLV and lagged duration of high volatility and their global counterparts, and country and decade fixed effects. We dually clustered standard errors at the country and year levels.

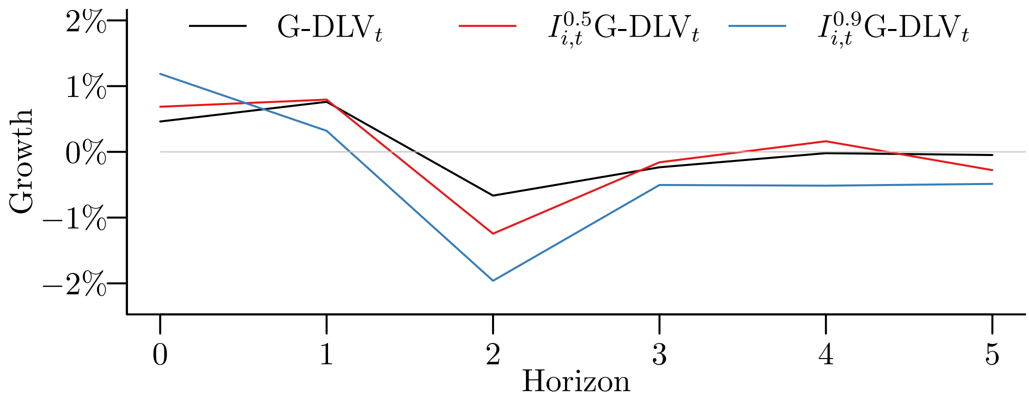


Figure 5 shows the estimated impulse responses for high credit states for different horizons based on quantiles 0.50 and 0.90. The growth reversal is more extreme in excessive credit states. Indeed, the results highlight an almost monotonic relationship between the amount of excessive credit and the impact of G-DLV on growth. In other words, 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 double that would otherwise be, and is longer lasting, making the overall impact negative. A one-year increase in G-DLV decreases economic growth 0.5% across the three-year cycle.

Taken together, these results provide support for our notion of credit-driven financial vulnerability. The boom-to-bust cycle driven by risk perceptions is especially strong in times of high credit growth. A country experiencing very high credit growth at levels that could be termed "excessive" is in a more vulnerable state, so that a longer lasting low-volatility environment have further negative consequences for growth, adversely amplifying the economic cycle.

3.5 Why does the persistence of low volatility affect economic growth?

So far, we have shown that a positive shock in the duration of a global low volatility environment has a robust boom-to-bust impact on a country's economic growth–that is, the persistence of low volatility has a short-run positive impact followed by a partial reversal. We surmise the reason lies in the particular interplay between risk-taking and growth through three primary channels: domestic investment, capital flows, and deterioration of lending standards due to increased risk appetite.

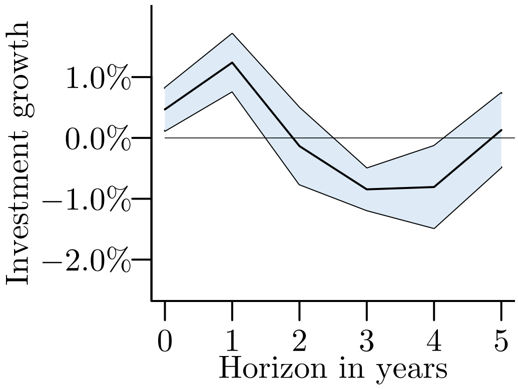
When investors perceive volatility as low globally, their risk appetite increases, so they are more inclined to reach for yield, partly manifested in a tilt of their asset allocations towards riskier countries or riskier asset classes. The result is an immediate increase in capital flows and investment and looser lending standards. Similarly, local investors, those engaged in capital projects, also increase their investments amid increased risk appetite. Eventually, with investment opportunities increasingly exhausted, the rate of investment, therefore, drops a few years later, along with capital flows.

To test our conjecture, we proxy private investment by gross capital formation (investment in fixed assets and inventories) as a percentage of GDP and obtain data from the World Development Indicators (WDI) for 74 countries from 1960 to 2012. Total capital inflows data for each country (as a percentage of GDP) are from the IMF, where the sample covers 55 countries from 1970 to 2012. Finally, to proxy the changes in lending standards, we use the high-yield issuance share index constructed by Kirti (2018). The index considers the aggregate share of high-yield bond issuance in a country and provides a proxy for debt-issuer quality. Accordingly, when lenders are willing to allocate a larger share of credit to less-creditworthy borrowers, the high-yield share index increases, indicating loose credit standards. Data include 38 countries with coverage going back to the early 1980s, at least for advanced countries.

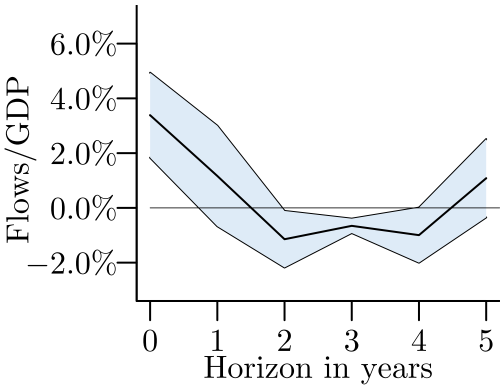
We run the baseline specifications (5) by replacing the endogenous variable economic growth with the growth of investment, capital flows, and high-yield share index as dependent variables. Besides the same controls we use in the baseline specifications (log GDP, inflation, and institutional quality of a country), we include the change in local short-term interest rates as they are expected to affect investment and capital flows. Because U.S. monetary policy decisions may also affect the relative return on investment in foreign economies, it may well affect cash flows across countries. However, including U.S. monetary policy surprises instead of a change in interest rates reduces our sample period significantly. Hence, we leave the analysis with the surprise series estimated by Romer and Romer (2004)

Figure 6: Impact of the persistence of global low volatility investment, capital flows, and lending standards.

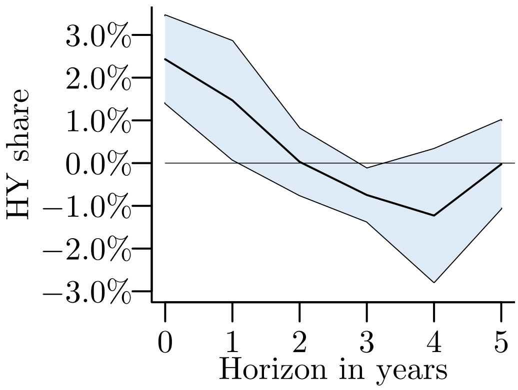
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of investment growth, capital inflows and lending standards to a shock to global duration of low volatility (introduced in Section 2.1). Private investment is 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 74 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 (2018). Data cover 38 countries from 1980 to 2016. We run regressions (5) by replacing growth, with capital flows, growth of investment, and the high-yield (HY) share index as dependent variables. All regressions include inflation rate, the degree of institutionalization of political competition, log-GDP per capita, GDP growth, change in short-term interest rates, lagged duration of low volatility (DLV) and lagged duration of high volatility and their global counterparts, and country and decade fixed effects. We dually clustered standard errors at the country and year levels.



(a) Shock to G-DLV



(b) Shock to G-DLV



(c) Shock to G-DLV

as a sensitivity analysis, reaching similar conclusions.[9]

[9] Romer and Romer (2004) narratively identify changes in the federal funds rate targets surrounding Federal Open Market Committe meetings. By regressing these target changes on the current rate and the Greenbook forecasts for output growth and inflation in the following two

Figure 6 shows that G-DLV has a strong impact on investment, capital flows, and lending standards, as seen in Panels (a), (b), and (c), respectively. As hypothesized, G-DLV has a positive contemporaneous impact, with a reversal a few years later. Specifically, if the world remains in a low-volatility environment an additional year, a typical country's investment growth, capital-flows-over-GDP ratio, and high-yield share will have an immediate increase of 0.47%, 3.34%, and 2.43% but a significant reversal of -0.9%, -0.66% and -0.75% in year three, respectively.

These results focus on global DLV because its impact on growth is more than four times stronger than the impact of local DLV, considering the whole sample. We then study the impact of local DLV on investment, capital flows, and lending quality. The results presented in Figure C1 in Appendix C indicate that the aggregate impact of local DLV is smaller than the G-DLV, and the amplitudes and statistical significances are much lower. This finding suggests that global investors allocate funds to other countries based on global financial conditions, rather than the local ones. Similarly, local DLV has no impact on investment growth and debt-issuer quality.

4 Robustness

We execute various robustness tests to check the sensitivity of our results. As a first robustness check, we estimate the volatility trend, which is used to calculate low volatility by applying the methodology recently proposed by Hamilton (2018). The estimated trend from the Hamilton filter is noisier than the estimates of the HP filter trend. To smooth them out, instead of keeping the last estimate for the trend at t, we calculate the mean of the previous 20-years' estimates.

Second, we examine whether our findings are robust to a different definition of volatility. Instead of estimating annual volatility as the standard deviation of 12 monthly real returns, we calculate volatility as the sum of absolute monthly returns.

Third, the primary analysis is conducted with those controls available for the full sample: inflation, log GDP, and institutional quality. We include various additional control variables. Short-term interest rates are expected to affect GDP, investment, and inflation. Thus, we collect three-month Treasury bill yields from the GFD. Moreover, Avdjiev et al. (2016) argue that the U.S. dollar has replaced the VIX as the variable most associated with an appetite for leverage; that when the dollar is strong, risk appetite is weak. Therefore, we include change in short-term interest rates and change in local exchange rates with respect to the U.S.

quarters, they can separate the natural policy response of the economy from the exogenous monetary policy surprise. The residuals from this estimation can be used as a proxy for monetary policy shocks in regression analysis.

dollar obtained from the GFD. Note that adding the two variables significantly reduces the sample size more than 60%, and, hence, we leave it as a robustness analysis.

Fourth, the recent literature on global financial cycles argues that the importance of U.S. monetary policy decisions drives risk appetite in the United States, affecting the VIX, which, in turn, shapes the global cycles on risk, asset prices, and credit (see for example, Rey, 2018). Hence, as a proxy for U.S. monetary policy decisions, we use the change in short-term U.S. interest rates as a global variable. Data are from the Jorda-Schularick-Taylor macrohistory database and cover from 1870 to 2016. Clearly, the changes in the interest rates are subject to endogeneity. Because the monetary policy changes could reflect a response to domestic and global macroeconomic developments, we as well control for the monetary policy surprise series estimated by Romer and Romer (2004) as the unexpected component, covering 1970 to 2008.

Fifth, in a recent paper, Baker et al. (2016) develop indexes of economic policy uncertainty (EPU) for a few countries around the world, including a historical EPU index for the United States going back to 1900. Similarly, Caldara and Iacoviello (2018) present a geopolitical risk index based on a tally of newspaper articles covering geopolitical tensions, again going back to 1900. We include both indexes, as we expect them to affect global risk appetite.

Sixth, we have an unbalanced panel, and global DLV is calculated as the weighted cross-sectional average of local DLVs available in a given year. To examine whether the unbalanced nature of data affects our findings, we repeat the analysis using the same countries every year. We choose current G7 constituents (United States, United Kingdom, France, Germany, Italy, Canada, and Japan) and started the sample period in the year when we have available stock market information for all of those countries, which is 1921, and recalculate global DLV.

Seventh, we check whether our results are robust to the chosen λ parameter. We consider various λs, but, as the results are qualitatively similar, only the estimated coefficients for $\lambda = 1{,}000$ are reported.

Finally, we test the robustness of our findings for the postwar era. Our sample contains many distinct subperiods, market structures, developments, and types of countries. The structure of financial markets was quite different for the early period, and stock markets become 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. For most of the early part of the sample, countries that would be classified today as developed dominate, but, as seen in Figure 1, the number of emerging countries starts to increase in the 1920s, further growing rapidly following the post World War II. We split our sample between developed and emerging countries classified by the IMF for the post-World War II period.

The results are reported in Table 3. To ease the interpretation of the results, instead of plotting impulse responses for all of the specifications, we present the estimated coefficients from (5) for both local and global volatility. Overall, we find that the main results are qualitatively unaltered under the various robustness checks.

During the postwar era, we find that both local and global volatility matters in explaining economic growth, while the impact of global volatility is significantly higher. The results are qualitatively similar to the whole period, supporting our findings. Moreover, persistent volatility has a similarly strong impact for both emerging and developed countries. Yet, the relative impact of global volatility on emerging countries is greater than on developed countries, while local volatility has a significantly greater impact on emerging ones. In both cases, the impact of global volatility is larger, similar to the baseline findings.

5 Conclusion

The financial sector plays a pivotal role in the macroeconomy, as has become increasingly apparent since the Global Financial Crisis. Many researchers have focused on the intersection between the financial system and the macroeconomy. We contribute to the literature by focusing on the attitude of economic agents towards risk as an essential driver of economic growth, especially distinguishing the asymmetric impact of the persistence of high and low volatility on growth.

We create a long and deep panel of countries, spanning almost one and a half centuries and 74 countries, and develop a methodology for identifying the persistence of low volatility, one we term as the duration of low volatility or DLV.

We reach several conclusions. The impact of the persistence of high volatility is what one might expect: an immediate fall in economic growth, but only over the short term. By contrast, the persistence of low volatility has a longer-term effect: initially positive but eventually followed by a reversal. The duration of global volatility matters much more than local. The cumulative effect of a longer low-volatility environment on growth is positive. However, that depends on the overall vulnerability of the financial system, especially regarding credit growth. If a country is in the highest decile of credit growth in a particular year, the amplitude of the reversal is double that would otherwise be; and is longer-lasting, making the overall effect negative.

Global volatility has a stronger impact on developing countries. Therefore, such countries particularly depend on global risk as they are rely on international capital flows for domestic investment.

The relationship between volatility and economic growth is stronger, especially during the past three decades, which is not surprising given the increased globalization and deregulation of financial markets since the end of Bretton Woods in 1972. Furthermore, our results confirm the importance of how U.S. financial markets affect growth throughout the world. When we use U.S. low volatility as a proxy for global DLV, we find a strong boom-to-bust effect on growth. However, such impact is only half as strong as the impact of global DLV that considers all other countries, and the one excluding the United States. Hence, while the United States is important, one can still argue it has limited effects on global cycles.

Table 1: Persistent low risk and economic growth: Granular Instrumental Variable approach

In this table, we compute the effects of global duration of low volatility (G-DLV) on economic growth by using the granular instrumental variable (GIV) estimator developed by Gabaix and Koijen (2019). In the first column, we present the first-stage regression results presented in (7). The dependent variable is G-DLV, introduced in Section 2.1. The next columns present the second-stage regression results in (8) for different horizons. All regressions include inflation rate, the degree of institutionalization of political competition, log-gross domestic product per capita, lagged duration of low volatility and the lagged duration of high volatility and their global counterparts, and country and decade fixed effects, but sake of brevity, estimated coefficients are omitted. ***, **, and * denote significance at the 1%, 5%, and 10% level (two sided), respectively.

	First stage	Second stage					
		h=0	h=1	h=2	h=3	h=4	h=5
GIV(G-DLV)	0.232***	4.198***	2.350***	-0.614*	-0.707**	-0.083	0.661*
	(0.023)	(0.290)	(0.316)	(0.332)	(0.331)	(0.332)	(0.342)
Observations	3161	3126	3062	2998	2934	2871	2808
adjusted R^2	0.56	0.20	0.08	0.05	0.06	0.07	0.06
F-statistic	79.08	17.53	7.30	5.51	5.92	6.27	5.64

Table 2: Persistent low risk and economic growth after Bretton Woods

The table shows the estimated impulse responses of the gross domestic product (GDP) growth rate to a shock to the duration of low volatility (DLV) and global duration of low volatility (G-DLV) for the post-Bretton Woods (BW) period (1972–2016) for all of the countries and emerging and developed countries, separated according to the International Monetary Fund classification. Moreover, we present the results when G-DLV is obtained by using (1) U.S. DLV estimates only, denoted by G-DLV$_{\mathrm{U.S.}}$, and (2) DLV estimates for all countries, except the United States, denoted by G-DLV$_{-\mathrm{U.S.}}$. Regressions include inflation rate, the degree of institutionalization of political competition, log-GDP per capita, lagged DLV and lagged duration of high volatility and their global counterparts, and country and decade fixed effects. All the standard errors are double clustered at the year and country levels. ***, **, and * denote significance at the 1%, 5%, and 10% level (two sided), respectively.

Countries	Shock	Period	h=0	h=1	h=2	h=3	h=4	h=5
All	G-DLV	1870–2016	0.390***	0.752***	-0.576**	-0.318	-0.091	-0.157
All	DLV	1870–2016	0.135***	0.149***	-0.124*	0.033	0.039	0.027
All	G-DLV	post–BW	0.406***	0.852***	-0.671***	-0.310	0.038	-0.039
All	DLV	post–BW	0.137**	0.171***	-0.159*	0.056	0.106**	0.022
All	G-DLV$_{\mathrm{U.S.}}$	post BW	0.227***	0.542***	-0.255**	-0.293**	-0.007	-0.042
All	G-DLV$_{-\mathrm{U.S.}}$	post BW	0.485***	0.962***	-0.739***	-0.311	0.079	-0.076
Emerging	G-DLV	post–BW	0.399***	1.049****	-0.591**	-0.418*	-0.005	-0.104
Emerging	DLV	post–BW	0.169**	0.179*	-0.240***	0.044	0.102*	0.040
Developed	G-DLV	post–BW	0.464***	0.638***	-0.756***	-0.117	0.144	-0.028
Developed	DLV	post–BW	0.082	0.165**	-0.106	0.042	0.057	-0.065

Table 3: Robustness

This table presents the robustness analysis. In column 1, we report whether the shock is to global or local duration of low volatility (G-DLV and DLV). In column 2, we report the type of robustness check. The rest of the columns report the results up to five periods ahead. First, we employ the method proposed by Hamilton (2018) instead of the Hodrick-Prescott (HP) filter to estimate the trend. Second, we estimate volatility as the sum of absolute monthly returns (Abs. ret.). Third, we include short-term interest rates (ΔINT_RATES) and change in exchange rates (ΔXR) in the control set. Fourth, to control for U.S. monetary policy decisions, we consider the short-term interest rates of the United States (USΔINT_RATES) as a global variable, and the monetary policy surprise series from Romer and Romer (2004) (MPsurprise). Fifth, we consider the economic policy uncertainty (EPU) index of Baker et al. (2016) and the geopolitical risk index (GPR) of Caldara and Iacoviello (2018) in the control set. Sixth, we use a balanced panel to obtain global duration of low risk (G7 constituents: United States, United Kingdom, France, Germany, Italy, Canada, and Japan) from 1921, which is the year we have available information for all of those countries. Seventh, we report the results when the smoothing parameter of the HP filter is set to 1,000 instead of 5,000. Finally, we examine our results for the post–World War II period (1946–2016), for emerging countries and for developed countries. All regressions include inflation rate, the degree of institutionalization of political competition, log-gross domestic product per capita, lagged DLV and lagged duration of high volatility and their global counterparts, and country and decade fixed effects. We dually clustered standard errors at the country and year levels. ***, **, and * denote significance at the 1%, 5%, and 10% level (two sided), respectively.

Shock	Robustness	h=0	h=1	h=2	h=3	h=4	h=5
G-DLV	Hamilton	0.301***	0.658***	-0.451**	-0.028	0.057	-0.075
DLV	Hamilton	0.095**	0.115**	-0.135**	0.048	0.068	0.083*
G-DLV	Abs. ret.	0.421***	0.683***	-0.613**	-0.397	-0.026	-0.147
DLV	Abs. ret.	0.121**	0.113**	-0.190**	0.047	-0.010	0.066
G-DLV	ΔINT_RATES/ΔXR	0.425***	0.796***	-0.698***	-0.182	0.053	-0.044
DLV	ΔINT_RATES/ΔXR	0.080	0.265***	-0.200**	0.003	0.073	-0.033
G-DLV	US ΔINT_RATES	0.254***	0.628***	-0.649***	-0.284	-0.060	-0.119
DLV	US ΔINT_RATES	0.107**	0.114**	-0.132*	0.044	0.050	0.036
G-DLV	MPsurprise	0.266*	0.836***	-0.700***	-0.101	0.188	-0.164
DLV	MPsurprise	0.116**	0.143***	-0.180**	0.078**	0.114*	0.017
G-DLV	EPU/GPR	0.385***	0.605***	-0.631***	-0.178	0.060	-0.268*
DLV	EPU/GPR	0.121**	0.098**	-0.116*	0.051	0.062	0.024
G-DLV	Balanced G7	0.272***	0.586***	-0.424**	-0.280	-0.014	0.024
DLV	Balanced G7	0.114*	0.168***	-0.140*	0.009	0.055	0.061
G-DLV	Lambda	0.418***	0.760***	-0.537**	-0.265	-0.133	-0.110
DLV	Lambda	0.130***	0.119**	-0.163**	0.028	0.093**	0.054
G-DLV	Post–WWII	0.336***	0.824***	-0.535**	-0.375	-0.076	-0.070
DLV	Post–WWII	0.110**	0.158***	-0.122	0.007	0.034	0.027
G-DLV	Emerging post–WWII	0.330***	0.948***	-0.553**	-0.516**	-0.150	-0.156
DLV	Emerging post–WWII	0.134**	0.129	-0.190**	0.003	0.019	0.049
G-DLV	Developed post–WWII	0.395***	0.743***	-0.511*	-0.190	0.001	-0.026
DLV	Developed post–WWII	0.094*	0.199**	-0.086	-0.014	-0.000	-0.039

Appendix A: Sample details

Table A1: Sample details
This table lists the countries in our sample, whether they are developed or emerging markets based on the International Monetary Fund classification, sample coverage, and the names of the market indixes. Source: Global Financial Data.[10]

Country	Classification	Coverage	Market
Argentina	Emerging	Jan. 1947–June 1958/	Argentina Swan, Culbertson and Fritz/
		Dec. 1966–Dec. 2010	Buenos Aires SE General (IVBNG)
Australia	Developed	Jan. 1875–Dec. 2016	Australia ASX All-Ordinaries
Austria	Developed	Jan. 1922–Dec. 2016	Wiener Boersekammer Share (WBKI)
Bahrain	Emerging	June 1990–Dec. 2016	Bahrain BSE Composite
Bangladesh	Emerging	Jan. 1990–Dec. 2016	Dhaka SE General
Belgium	Developed	Jan. 1897–Dec. 2016	Brussels All-Share Price
Brazil	Emerging	Jan. 1955–Feb. 1993/	Rio de Janeiro Bolsa de Valores (IBV)/
		Apr. 1993–Dec. 2010	BOVESPA
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	Dec. 1990–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	Crotia Bourse (CROBEX)
Denmark	Developed	Jan. 1921–Dec. 2016	OMX Copenhagen All-Share Price
Ecuador	Emerging	Jan. 1994–Dec. 2016	Ecuador Bolsa de Valores de Guayaquil
Egypt	Emerging	Jan. 1950–Sept. 1962/	Egyptian SE/
		Dec. 1992–Dec. 2010	Cairo SE EFG General
El Salvador	Emerging	Dec. 2003– Dec. 2014	El Salvador Stock Market
Finland	Developed	Jan. 1920–Dec. 2010	OMX Helsinki All-Share Price
France	Developed	Jan. 1870–Dec. 2010	France CAC All-Tradable
Germany	Developed	Jan. 1870–Dec. 2010	Germany CDAX Composite
Ghana	Emerging	Nov. 1990–Oct. 2010	Ghana SE Databank/
			Ghana SE Composite
Greece	Developed	Dec. 1928–Sept. 1940/	Greece Stock Market/
		Dec. 1952–Dec. 2010	Athens SE General
Hungary	Emerging	Dec. 1924–Mar. 1948/	Hungary Stock Market/
		May 2002–Dec. 2010	OETEB Hungary Traded
Iceland	Developed	Dec. 1992–Dec. 2010	OMX Iceland All-Share Price
India	Emerging	Jan. 1922–Dec. 2010	Bombay SE Sensitive
Indonesia	Emerging	Jan. 1983–Dec. 2010	Jakarta SE Composite
Iran	Emerging	Mar. 1990–Dec. 2016	Tehran SE Price (TEPIX)
Ireland	Developed	Jan. 1934–Dec. 2010	Ireland ISEQ Overall Price
Italy	Developed	Sept. 1905–Dec. 2010	Banca Commerciale Italiana

Table A1: Sample details (cont.)

Country	Classification	Coverage	Market
Japan	Developed	July 1914–Dec. 2010	Tokyo SE Price (TOPIX)
Kazakhstan	Emerging	July 2000–Dec. 2016	Kazakhstan SE KASE
Kenya	Emerging	Jan. 1964–Dec. 2010	Nairobi SE
Korea	Developed	Jan. 1962–Dec. 2010	Korea SE Stock Price (KOSPI)
Kuwait	Emerging	Oct. 1975–Dec. 1987/	Kuwait SE Indec
Malaysia	Emerging	Dec. 1973–Dec. 2010	Malaysia KLSE Composite
Mauritius	Emerging	July 1989–Dec. 2010	SE of Mauritius (SEMDEX)
Mexico	Emerging	Jan. 1931–Dec. 2010	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. 2010	Casablanca Financial Group 25 Share
Netherlands	Developed	Jan. 1919–Dec. 2010	Netherlands All-Share Price
New Zealand	Developed	Jan. 1931–Dec. 2010	New Zealand SE All-Share Capital
Nigeria	Emerging	Jan. 1988–Dec. 2010	Nigeria SE
Norway	Developed	Jan. 1914–Dec. 2010	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
Argentina	Emerging	Jan. 1947–June 1958/	Argentina Swan, Culbertson and Fritz/
		Dec. 1966–Dec. 2010	Buenos Aires SE General (IVBNG)
Poland	Emerging	Jan. 1921–Dec. 1939/	Warsaw SE 20-Share Composite/
		Apr. 1994–Dec. 2016	
Portugal	Developed	Jan. 1933–Dec. 2010	Oporto PSI-20
Qatar	Emerging	Dec. 1995–Dec. 2016	Qatar SE
Romania	Emerging	May 1998–Dec. 2010	Bucharest SE Composite
Russia	Emerging	Sept. 1993–Dec. 2010	Russia AK&M Composite (50 shares)
Saudi Arabia	Emerging	Feb. 1985–Dec. 2016	Saudi Arabia Tadawul SE
Singapore	Developed	July 1965–Dec. 2010	Singapore FTSE Straits-Times
South Africa	Emerging	Jan. 1910–Dec. 2010	FTSE/JSE All-Share
Spain	Developed	Dec. 1914–Dec. 2010	Madrid SE General
Sri Lanka	Emerging	Dec. 1984–Dec. 2010	Colombo SE All-Share
Sweden	Developed	Jan. 1906–Dec. 2010	Sweden OMX Affärsvärldens General
Switzerland	Developed	Jan. 1916–Dec. 2010	Switzerland Price
Thailand	Emerging	Apr. 1975–Dec. 2010	Thailand SET General
Tunisia	Emerging	Dec. 1997–Dec. 2010	Tunisia SE
Turkey	Emerging	Jan. 1986–Dec. 2010	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. 1870–Dec. 2010	UK FTSE All-Share
United States	Developed	Jan. 1870–Dec. 2010	S&P 500 Composite Price
Uruguay	Emerging	Jan. 1925–Dec. 1995/	Uruguay SE/
		Jan. 2008–Dec. 2010	Bolsa de Valores de Montevideo
Venezuela	Emerging	Jan. 1937–Dec. 2010	Caracas SE General
Zambia	Emerging	Dec. 1996–Dec. 2010	Zambia Lusaka All-Share (LASI)

Appendix B: Data definitions and sources

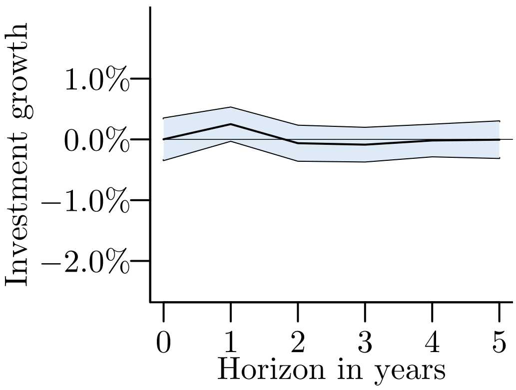
- $\text{DLV}_{i,t}$: Duration of low volatility is calculated as the number of years in which stock market volatility remains low for country i in year t. Volatility is annual realized volatility–the standard deviation of real monthly stock market returns over a year. Monthly stock market indexes are collected from Global Financial Data (GFD), with data available for 74 countries, spanning 1870 to 2016. Data coverage is listed in Table A1.
- G-DLV_t: Global DLV is calculated as the GDP-weighted cross-sectional averages of local DLVs ($\text{DLV}_{i,t}$).
- $\text{DHV}_{i,t}$: Duration of high volatility is calculated as the number of years in which stock market volatility remains high for country i in year t.
- G-DHV_t: Global DHV is calculated as the the GDP-weighted cross-sectional averages of local DHVs ($\text{DHV}_{i,t}$).
- 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 1870 to 2014.
- Log GDP: log per-capita income. Data from the Maddison project cover 72 countries from 1870 to 2014.
- INF: Inflation rate calculated as the annual percentage change of the consumer price index. Data are from the GFD.
- POLCOMP: Political competition as a proxy for institutional quality. Data are from the Polity IV Project database. POLCOMP is the combination of the degree of institutionalization or regulation of political competition and the extent of government restriction on political competition. The higher the value of the POLCOMP, the better the institutional quality of a given country.
- Δ INT_RATES: Change in local three-month Treasury yields. Data are for 61 countries over 1900 to 2016, obtained from the GFD.
- ΔXR: Change in exchange rates. Local currency with respect to U.S. dollar. Data are for 58 countries over 1801 to 2010, obtained from the GFD.
- MPsurprise: U.S. monetary policy shocks introduced in Romer and Romer (2004). The authors use the FED Greenbook forecasts of output growth and inflation along with the fed funds rates to estimate shocks. Sample covers 1970 to 2008.
- Flows/GDP: Total capital 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 74 countries.
- HY share: Lending standards are proxied via the high-yield bond issuance data constructed by Kirti (2018). Data cover 38 countries from 1980 to 2016.

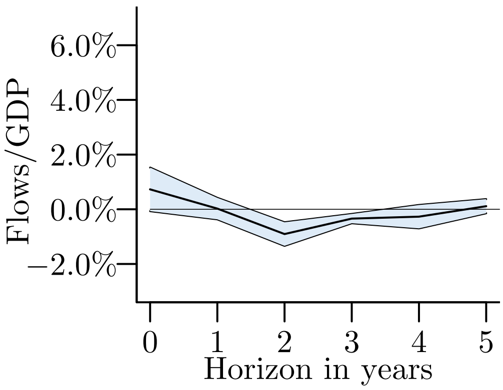
Appendix C

Figure C1: Impact of persistent local low volatility investment, capital flows, and lending standards.

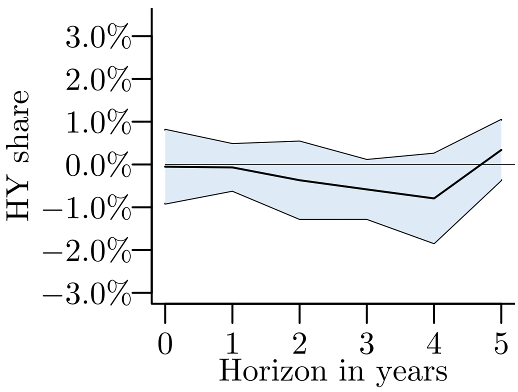
This figure shows the estimated impulse response functions using Jordà's (2005) local projections along with its associated 95% confidence band of investment growth, capital inflows, and lending standards to a shock to local duration of low volatility (DLV), which is introduced in Section 2.1. Private 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 74 countries from 1960 to 2012. Total capital inflows data (as a percentage of GDP) are obtained from International Monetary Fund for 55 countries from 1970 to 2012. Lending standards are proxied via the high-yield bond issuance data constructed by Kirti (2018). Data cover 38 countries from 1980 to 2016. We run regressions (5) by replacing growth, with capital flows, growth of investment, and the high-yield (HY) share index as dependent variables. All regressions include inflation rate, the degree of institutionalization of political competition, log-GDP per capita, GDP growth, change in short-term interest rates, lagged DLV and lagged duration of high volatility and their global counterparts, and country and decade fixed effects. We dually clustered standard errors at the country and year levels.



(a) Shock to local DLV



(b) Shock to local DLV



(c) Shock to local DLV

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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Systemic Risk Centre

The London School of Economics
and Political Science
Houghton Street
London WC2A 2AE
United Kingdom

tel: +44 (0)20 7405 7686
systemicrisk.ac.uk
src@lse.ac.uk