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The Riskiness of Credit Origins and Downside Risks to Economic Activity

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ABSTRACT: We construct a country-level indicator capturing the extent to which aggregate bank credit growth originates from banks with a relatively riskier profile, which we label the Riskiness of Credit Origins (RCO). Using bank-level data from 42 countries over more than two decades, we document that RCO variations over time are a feature of the credit cycle. RCO also robustly predicts downside risks to GDP growth even after controlling for aggregate bank credit growth and financial conditions, among other determinants. RCO's explanatory power comes from its relationship with asset quality, investor and banking sector sentiment, as well as future banking sector resilience. Our findings underscore the importance of bank heterogeneity for theories of the credit cycle and financial stability policy.

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Authors' email addresses:	clraddatz@fen.uchile.cl; dseneviratne@IMF.org; jvandenbussche@IMF.org; xiepeichu@gmail.com; yxu@IMF.org

* Claudio Raddatz (Universidad de Chile); Dulani Seneviratne, Jérôme Vandenbussche, and Yizhi Xu (International Monetary Fund); and Peichu Xie (Citadel LLC).

WORKING PAPERS

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Contents

Acronyms/Glossary

BLS .... Bank Lending Standards
CA .... Current Account
EDF .... Expected Default Frequency
FCI .... Financial Conditions Index
GDP .... Gross Domestic Product
GFC............ Global Financial Crisis
GUO .... Global Ultimate Owner
IFS .... International Financial Statistics
LLP .... Loan Loss Provisions
OLS............. Ordinary Least Squares
NPL............. Nonperforming Loans
RCA .... Riskiness of Credit Allocation
RCO............ Riskiness of Credit Origins

I. Introduction

Abundant empirical evidence supports the view that periods of large aggregate credit expansions tend to be followed by adverse macroeconomic outcomes and the occurrence of financial crises (Jorda et al. 2011, Schularick and Taylor 2012, Mian et al. 2018, among others), especially when the credit expansion takes place in an environment of easy financial conditions and buoyant credit sentiment (Krishnamurthy and Muir 2017, López-Salido et al. 2017, Adrian et al. 2022, Greenwood et al. 2022). However, existing cross-country empirical studies focus on aggregate measures of the volume and price of credit and leave aside the role that the composition of credit origination and lender heterogeneity may play in aggregate risk-taking and financial stability.

Anecdotal evidence suggests that faster bank-level credit growth during a boom is associated with worse performance during the ensuing bust and that the strength of financial institutions driving the expansion matters for future aggregate outcomes. During the Global Financial Crisis (GFC), several iconic failures were financial intermediaries that had followed a very aggressive expansion strategy. In the United States, Countrywide Financial and Washington Mutual became the first and third largest mortgage originators over a short period before the crisis, lost billions on subprime exposures, and had to be resolved in 2008 (United States Senate, 2010). Spanish savings banks, which were at the epicenter of the Spanish banking crisis a decade ago, had experienced a continuous rise in their loan market share in the run-up to the crisis (Santos, 2018). Anglo-Irish Bank, the only Irish bank nationalized during the Irish banking crisis of 2008-2010, had the fastest pre-crisis credit growth among major Irish banks (Regling and Watson, 2010). Going further back in time, during the credit boom in Finland and Sweden in the early 1990s, the most aggressive lenders were the weakest in capitalization and underlying profitability (Englund and Vihriala, 2010).

Theoretical models of financial amplification and financial crises have long recognized the importance of accounting for heterogeneity across economic agents (Bernanke and Gertler 1989; Kiyotaki and Moore 1997; Brunnermeier and Sanikov 2014)[2]. It is only recently that some macrofinancial models have focused on heterogeneity across financial intermediaries and shown how this heterogeneity matters for the dynamics of aggregate risk-taking and financial stability (Geanakoplos 2010, Korinek and Nowak 2017, Coimbra and Rey 2018 and 2023).

In this paper, we provide novel empirical evidence that the extent to which the growth in aggregate bank lending activity concentrates in riskier banks varies over the credit cycle and, more importantly, that it helps predict downside risks to economic growth.[3] Furthermore, we provide country-level and bank-level analyses to explore the mechanisms underlying our key result.

Specifically, using a large sample of 3071 banks across 42 countries over the 1990–2019 period, we construct an aggregate measure of the extent to which credit is originated by relatively riskier banks (as measured by the within-country, relative z-score), taking inspiration from the approach of Greenwood and Hanson (2013) for

[2] These models generally impose conditions that lead to the separation of heterogeneous agents in borrowers, lenders, or intermediaries in equilibrium. Most traditional models either assume that each sector is represented by a single agent or that there is perfect risk sharing within a sector, so that heterogeneity within a sector—that is. across borrowers or financial intermediaries—does not matter.

[3] In the paper, we use the expressions “riskier bank” and “weaker bank” interchangeably.

capturing the composition of aggregate debt issuance across heterogeneous borrowers. We present evidence that our measure, which we label the Riskiness of Credit Origins (RCO), rises when aggregate credit growth increases and when financial conditions become looser. In addition, we provide complementary bank-level evidence documenting the underlying mechanism at the micro level. These patterns in the cross-section of bank risk-taking over the credit cycle captured or proxied by RCO are not only of intrinsic interest as a characterization of the cycle, but they also help shed further light on why large credit expansions present a risk for financial stability.

We show that an increase in RCO predicts downside risks to GDP growth, even after controlling for key determinants previously highlighted in the literature, including aggregate credit growth and financial conditions. The magnitude of the effects we document is sizable. A one-standard-deviation increase in RCO shifts the left tail of the average cumulative two-year-ahead GDP growth distribution by about 30 basis point in our baseline specification. Our findings are robust to a battery of robustness tests that include using additional controls (including an aggregate measure of banking sector riskiness), an alternative measure of bank-level riskiness, a restricted sample of banks in the analysis, or an alternative quantile regression estimation method.

Finally, we explore three possible —and somewhat related— channels underlying our key finding. We first examine a credit quality channel. At the micro level, we investigate whether riskier banks lend more to riskier borrowers, leading to a weaker future loan portfolio performance, and how this relationship depends on bank-level relative credit growth. We document that banks that expand credit relatively faster experience a greater increase in loan loss provisions and nonperforming loan ratios later and that this increase is even stronger when the bank is ex-ante riskier (that is, when it has a lower relative z-score). At the macro level, we also analyze whether RCO's explanatory power for downside risks to growth is affected by the inclusion of a variable capturing a riskier allocation of credit (Brandao Marques et al. 2022) in the specification. We find that it does at horizons up to two years.

A second plausible channel is sentiment. In the spirit of López-Salido et al. (2017) who proxy credit sentiment by financial variables that predict future changes in credit spreads, we examine whether RCO predicts future changes in aggregate bank lending standards and financial conditions. We find that it does at horizons up to two years for bank lending standards and financial conditions. Both findings strongly support a sentiment channel.[4]

Finally, RCO could capture a dimension of aggregate banking sector vulnerability related to the distribution of bank-level vulnerabilities. By construction, RCO measures the extent to which banks that are relatively riskier contribute to the expansion of banking sector credit. While the relative nature of the inputs to the measure does not imply a mechanical relationship, we speculate that periods when RCO is elevated, especially if they persist, could result in a larger fraction of an economy's loan portfolio being concentrated in riskier banks. To the extent that riskier banks are more likely to reduce their lending in the future in response to an adverse shock, and that borrowers face frictions when trying to shift lenders, this could result in an aggregate contraction in lending and activity. In support of the existence of this third channel, we find that bank riskiness is a determinant of future bank-level lending activity following large negative shocks. We also find that RCO predicts leftward shifts of the

[4] Note that although the credit quality and banking sector sentiment channels bear some resemblance, they are conceptually distinct. In the credit quality channel, poor future aggregate performance is due to a deterioration of lending quality by riskier banks. In the banking sector sentiment channel, poor future aggregate performance is could be due a deterioration in lending quality across the board.

extreme left tail of banking sector stock returns, which is also consistent with the presence of a resilience channel.[5]

The rest of the paper is structured as follows. Section II discusses the theoretical underpinnings of the relationship between bank riskiness, risk-taking, and credit cycle, and reviews the relevant theoretical and empirical literatures. Section III introduces our measure of the RCO. Section IV analyzes its co-movement with aggregate changes in bank credit and provides related bank-level evidence. Section V documents RCO's predictive power for future downside risks to growth while Section VI presents our analysis of the three possible channels underlying this relationship. Section VII concludes. Appendices provide additional information on data sources, variables construction, sample construction, and additional robustness analyses.

II. Theoretical Underpinnings and Further Links to the Literature

The relationship between bank riskiness —the probability that a bank will default on its obligations— and risk-taking is theoretically ambiguous. On the one hand, classic risk-shifting incentives due to limited liability (Jensen and Meckling 1976) naturally generate a positive association between the two.[6] In addition, low bank capitalization reduces the incentives to monitor loan quality because of market imperfections (Holmstrom and Tirole 1997; Allen et al. 2011).[7] Even if bank creditors are aware of these incentives and ask for compensation through a higher cost of bank debt or attempt to exert discipline on managers through greater reliance on runnable demand deposits (Calomiris and Kahn 1991; Diamond and Rajan 2000, 2001), the existence of deposit insurance or implicit government guarantees could limit market discipline or efficiency (Gorton and Huang, 2004; Farhi and Tirole, 2012). On the other hand, the threat of runs may be a strong incentive for banks to avoid risk-shifting behavior (Jacklin and Battacharya, 1988; Diamond and Rajan, 2000; Iyer et al., 2016). The ability of bondholders to impose covenants (Ashcraft, 2008) or regulatory constraints may also limit the ability of banks to take risks (Dewatripont and Tirole 2012).

Regardless of the sign of the relationship between bank riskiness and risk-taking in ordinary bank credit market conditions, riskier banks' incentives for risk-taking are likely relatively greater during buoyant aggregate credit expansions for various reasons. First, theoretical models with rational agents indicate that lending standards are procyclical because of endogenous variation in the profitability of screening or the information on the quality composition of borrowers (Ruckes 2004; Dell'Ariccia and Marquez 2006), or because of loss in institutional memory (Berger and Udell 2004). Since screening benefits are arguably lower for weaker banks because of the

[5] We also explore whether RCO's predictive power for downside risks to growth is affected by the inclusion of the skewness of the distribution of bank leverage (Coimbra and Rey, 2018) in the specification, and find no consistent evidence that it does. As a by-product, we also find that the leverage skewness measure is not statistically significant in our regression results.

[6] Like other types of firms, banks protected by limited liability have such incentives because of the option value of equity: a bank taking a risk will reap the benefits when the gamble pays off and will leave its creditors holding the bucket when it does not. These incentives are stronger when bank solvency is lower.

[7] Conversely, under limited liability, banks with higher risk appetite choose to be more leveraged and riskier (Coimbra and Rey, 2023).

debt overhang problem (Myers 1977), the relaxation of standards in good times is likely stronger among them. In Coimbra and Rey (2023), lower aggregate funding costs encourage banks with a higher risk appetite to expand their credit provision and leverage relatively more. Second, with boundedly rational agents, the price of risk is too low during the expansionary phase of the credit cycle because of diagnostic expectations (Bordalo et al. 2018) or neglect of crash risk (Baron and Xiong 2017). The resulting easier access to debt financing would facilitate risk-taking by banks with relatively higher incentives to engage in this behavior.

Altogether, these theoretical considerations suggest that the credit cycle should be an important driver of cross-sectional differences in bank risk-taking through loan portfolio growth, which is what our RCO measure captures. Yet this hypothesis has so far remained untested. Coimbra and Rey (2018) construct the within-country skewness of the leverage distribution across banks. Their indicator is an aggregate measure of banking sector riskiness based on a single dimension (bank leverage), while ours captures two dimensions by combining the bank-level riskiness dimension with information on the flow of credit to create an indicator of the RCO at any given point in time.

On the empirical side, our cyclicality analysis relates to prior bank-level evidence suggesting an association between bank riskiness and bank risk-taking. Igan and Tamirisa (2008) and Igan and Pinheiro (2011) find that weaker banks grow their loan portfolios more slowly than stronger banks in normal times but grow them at the same pace as other banks during credit booms. Our loan growth regression results echo theirs, but our empirical specification is more parsimonious, and our key macro driver is aggregate credit growth rather than a dummy capturing episodes of credit booms. Our cyclicality analysis also relates to the literature on the risk-taking channel of monetary policy, in which various papers have used granular supervisory data to show that looser monetary policy induces banks to take more risk and that this effect depends on bank solvency (Jimenez et al. 2014, Dell'Ariccia et al. 2017). We complement this literature by focusing on a broader sample of countries and on the credit cycle rather than on changes in monetary policy.

The main analysis in our paper relating RCO to downside risks to GDP growth is directly connected to the banking crisis literature (Gourinchas et al. 2001, Obstfeld 2012, Schularick and Taylor 2012, Dell'Ariccia et al. 2016, Jordà et al. 2021, among others) and the growth-at-risk literature (Giglio et al. 2016, Adrian et al. 2019, Adrian et al. 2022) which have investigated the role played by aggregate credit growth, financial conditions, and standard aggregate banking soundness indicators in driving adverse macrofinancial outcomes. We add to these literatures by demonstrating the important role of the origins of bank credit.

Our micro analysis of the asset quality channel builds on several empirical papers that have examined the bank-level relationship between size of loan growth and subdued future performance. These papers have shown that banks whose loan portfolio grows fastest (relative to domestic peers) suffer from a relatively weaker performance within a few years, regardless of whether performance is measured by the non-performing loan ratio (Jimenez and Saurina 2006; Chavan and Gambacorta 2019), loan loss provisions (Foos et al. 2010), stock returns, or return on assets (Fahlenbrach et al. 2018). We complement these studies, all focused on single countries, by examining this relationship in a broad sample of countries and, most importantly, by showing that bank-level riskiness amplifies the effect of relative size of loan portfolio growth in affecting future performance. In addition, in a smaller sample of banks, we document that ex ante credit quality (measured by the share of leveraged loans issuance in total loan issuance) is greater in banks that are riskier and grow their loan book relatively faster. Our discussion of the asset quality channel at the country level relates to the macro literature on lending standards and GDP growth (Greenwood and Hanson 2013, Kirti 2018, Brandao Marques et al. 2022).

Our discussion of the resilience channel is indirectly related to the micro literature on relationship banking, which has extensively documented the costs of switching banks for borrowers (James 1987; and Petersen and Rajan 1994; Elyasani and Goldberg 2004; Hubbard et al. 2002; Schwert 2018). At the macro level, Coimbra and Rey (2018) show that aggregate credit growth is more responsive to funding costs when the skewness of the bank leverage distribution increases. By contrast with our work, Coimbra and Rey (2023) do not relate their indicator to financial stability outcome variables, as we do.

While the typical interpretation in the literature of the positive relationship between credit growth and future recessions or crises has been that faster credit growth implies higher financial vulnerabilities because of higher leverage in the economy, the evidence we provide also suggests that composition effects erode banking sector resilience during the upward phase of the credit cycle as the relatively more fragile banks' contributions to credit growth and risk-taking increase. Such composition effect is a feature of Korinek and Nowak (2017)'s model, in which, because of imperfect risk-sharing, a sequence of positive aggregate shocks allows the market share of intermediaries with a higher risk appetite to grow organically and, therefore, increases the vulnerability of the economy to bad shocks.

III. Riskiness Of Credit Origins Measurement and Samples Construction

Measuring the Riskiness of Credit Origins

We measure the RCO based on the approach of Greenwood and Hanson (2013) for nonfinancial firms in the United States. This approach consists of four steps, which we apply to banks for each country-year in our sample. First, we sort these banks into deciles according to an indicator of their riskiness and assign each bank its decile position in the distribution (a higher decile corresponding to higher riskiness). Second, we sort all banks into two groups according to their annual loan growth and classify all banks with loan growth equal to or above (below) the median as top (bottom) lenders. Third, we compute the average lagged riskiness decile among top and bottom lenders.[8] Finally, we take the difference between these two averages. Formally, the measure is defined as follows:

$$RCO_{c,t} = \frac{1}{N_{c,t}^{Top}} \sum_{i \in Top_{c,t}} Risk(decile)_{i,c,t-1} - \frac{1}{N_{c,t}^{Bottom}} \sum_{i \in Bottom_{c,t}} Risk(decile)_{i,c,t-1} \tag{1}$$

where $Risk(decile)_{i,c,t-1}$ is the decile in the distribution of bank *i*'s riskiness measure in country *c* at time *t-1*, $N_{c,t}^{Top}$ and $N_{c,t}^{Bottom}$ are the number of banks in the top and bottom half of the distribution of loan growth in country *c* at time *t*, respectively. Because the paper focuses on the dynamics of RCO within countries and not

[8] We obtain very similar results if we use the contemporaneous riskiness decile instead of its lagged value in the country-level analysis presented later in the paper.

on its cross-country variation, we normalize this raw measure by subtracting its country-specific mean. This adjustment removes the influence of the country-specific sectoral composition of banks and ensures greater cross-country comparability. An increase in RCO signals that banks expanding lending relatively faster are riskier, indicating a riskier aggregate origin of credit. By construction, the units of RCO correspond to deciles, so a value of 1 indicates that top issuers have an average riskiness which is one decile above that of bottom issuers.

Following the banking literature, our baseline measure of bank riskiness is the opposite of a bank's z-score, defined as the sum of the return on average assets and the leverage ratio, divided by the historical (three-year) standard deviation of returns on average assets.[9] The z-score captures the extent to which a bank's current income and equity capital can absorb fluctuations in income, so a higher value indicates a safer bank. For its opposite, a higher (less negative) value indicates a riskier bank.

As an alternative to the z-score, we also construct a measure of bank riskiness based on balance sheet indicators of bank fundamentals. Following the literature, we consider the following set of bank fundamentals related to the CAMEL/CAEL ratings approach initially developed by U.S. bank supervisors (see Purnandaram, 2007): (i) capital adequacy , captured by the principal component of a bank's ratio of total equity to total assets and its z-score (as defined above) ; (ii) the ratio of loan loss provisions to total assets capturing asset quality; (iii) the return on average assets as a measure of profitability; (iv) the cost-to-income ratio as a proxy for efficiency; and (v) liquidity, captured by the principal component of a bank's ratios of loans to assets, loans to deposits, liquid assets to total assets, and liquid assets to deposits. We construct this composite measure of riskiness by running an ordinary least squares regression relating these bank fundamentals to the (log) expected default frequency (EDF) for the subsample of banks for which we have EDF data. The regressions include country-year fixed effects, so the coefficients for the various fundamentals explain the within country-year variation in EDF. We then use the estimated coefficients for the fundamentals to project bank riskiness for all the banks in our sample that report data for the included fundamentals (including those without EDF data). In doing the projection we do not include the estimated country-year fixed effects, so the predicted values are scale free and only reflect the within country-year relative ranking of bank riskiness. For this reason, we also center the estimates to have a zero mean within a country. We refer to this measure as a "synthetic EDF" (see Appendix 2 for a detailed explanation).

Data Sources, Samples Construction, and Descriptive Statistics

We source banks' financial statement data from Fitch Connect. We merge two vintages to increase coverage in the time dimension (data downloads in June 2018 and March 2021).[10] The financial statements are first filtered and cleaned based on bank specialization and market description and by imposing some basic requirements on key balance sheet ratios and removing duplicates. We build historical time series of consolidated financial statements and merge these data with historical ownership data (sourced from Orbis Historical and IMF (2015)) and mergers and acquisitions data (sourced from Orbis M&A).[11] The ownership data is used to drop

[9] See Laeven & Levine (2009), Demirgüç-Kunt and Huizinga (2010), Beck et al. (2013), Garel and Petit-Romec (2017), Khan et al. (2017), and Altunbas et al. (2018), among others for the use of z-score in this literature.

[10] Banks that ceased to exist in the early part of the sample period had been removed from the FitchConnect database at the time of the March 2021 download. We "add them back" using data from the June 2018 download.

[11] In cases of mergers and acquisitions, we maintain the acquiring bank in our sample and flag the year of the acquisition. These bank-years are not included in the econometric analysis.

subsidiaries when the parent bank is in the same country and in the sample to avoid double counting. Data on banks' EDF are from Moody's CreditEdge (see Appendix 3 for further details).

Since our analysis focuses on the dynamics of the within-country distribution of loan growth, we restrict our sample to countries with a sufficiently large number of banks per year over a reasonably long period. The construction of our baseline sample starts by including only banks with total assets above 0.5 percent of the total assets of their country's largest bank during at least one year and with at least five years of data. This allows us to drop small banks without imposing an absolute asset size threshold that may be inadequate in a cross-country setting. Next, for each country, we keep only those years with at least ten banks meeting the criteria above, count the number of such years per country, and keep only those countries with at least five years meeting all these conditions in our sample. Finally, we keep only those countries where we could build a financial conditions index (FCI, see description below) because the recent macrofinancial literature on the credit cycle has emphasized the importance of considering price-based measures of the state of the cycle.[12] This process yields a sample with 44,515 total bank-year observations, out of which 39,730 have the required information to construct the z-score. These observations come from 3,071 banks in 42 countries from 1990 to 2019 (the list of countries is provided in Appendix 1). We also construct a restricted sample considering only country-years with at least 20 banks satisfying the criteria listed above and check the robustness of our results in this sample.

Macrofinancial data sources, definitions, and transformations used in the paper are summarized in Appendix 3. Our baseline credit series is sourced from the IMF's International Financial Statistics (IFS) and captures the credit to the private sector from domestic money banks. We prefer it to alternative sources because it provides the greatest coverage. Other standard macroeconomic series, such as nominal GDP, real GDP and current account, are also sourced from IFS. We estimate FCIs for 1990–2019 at a quarterly frequency using a set of eight price-based financial indicators: (1) term spread; (2) corporate spread; (3) sovereign spread; (4) interbank spread; (5) first difference in real long-term rate; (6) equity returns; (7) equity volatility; and (8) house price returns. We use the annual average of quarterly FCIs for each country as a measure of financial conditions during each year. We also use country-level data series on the riskiness of credit allocation (RCA), which captures the extent to which corporate credit in a country flows to relatively riskier firms, and which we constructed based on Brandao-Marques et al. (2022) using Worldscope data.

Table 1 reports summary statistics for our baseline sample, both for bank-level variables (Panel A) and country-level variables (Panel B). At the bank level, the average z-score is 147 for the overall sample. This figure indicates that the typical bank operates with a stock and flow of potential capital resources two orders of magnitude larger than its annual income's near-term historical standard deviation. There is important variation across observations, with the median bank-year having a z-score of 59 during the sample period and 25 percent of the bank-years showing a z-score of 25 or less. Less than 1 percent of the observations have a z-score smaller than 1. By construction, the synthetic EDF riskiness measure has a zero average, so it is more relevant to focus on its variation. The standard deviation of this variable across all observations is 0.3, which is very similar to its interquartile range. Annual nominal loan growth (measured in local currency terms) has an overall average of 7.8 percent, and its standard deviation is more than twice as large, indicating substantial variation. Loan loss provisions (LLP) and nonperforming loans (NPL), both expressed as a share of lagged

[12] See Krishnamurthy & Muir (2017), López-Salido et al. (2017), and Adrian et al. (2019) and among others.

gross loans, have an overall average of 1 and 4.4 percent, and the average change in NPL (expressed as a percentage of lagged gross loans and labeled (Δ(NPL)) is 0.2 percent.

Turning to the macroeconomic variables reported in Panel B, across country-years, the change in the ratio of total credit to GDP averages 1.1 percent, has a standard deviation of 4.9 percent, and an interquartile range of 4.4 percent, thus exhibiting significant variation. By construction, the FCI has a mean of zero and a standard deviation of 1.

The RCO measures have a zero mean, so the relevant summary statistics describe their variation. For the baseline measure based on the z-score, the standard deviation across country-years is 1.3 with an interquartile range of 1.6. The corresponding values for the alternative measure based on the synthetic EDF are 1.4 and 1.8.

The Cyclicality of the Riskiness of Credit Origins

Before delving into a formal analysis of the drivers of RCO, we present in Figure 1 the evolution of RCO across our sample of countries and for selected countries during our sample period. Panel A shows the evolution of the cross-country distribution of RCO constructed from our baseline measure of riskiness (z-score), and Panel B shows the evolution of RCO based on our alternative measure (synthetic EDF). It is apparent that, at a global level, RCO increased before the dot-com boom of the late 1990s, declined in its aftermath, rose again in the run-up to the global financial crisis, plateaued during the crisis, and dropped abruptly during the euro area sovereign debt crisis.

This broad global dynamic is also present at the individual country level, with some country-specific nuances. Panels C to F show the evolution of the measure for the United States, Germany, Ireland, and Spain, respectively. In the United States, RCO dropped significantly during the GFC and its immediate aftermath and rebounded strongly afterward. By contrast, there was no post-GFC rise in Germany. In Ireland, the post dot-com boom decline was only a blip, and RCO rose almost non-stop from the late 1990’s to the onset of the GFC in 2007. Spain had one additional RCO cycle late in the sample period compared to the other three countries, with a spike in 2015 after fully emerging from its earlier financial crisis.

To formally confirm these apparent cyclical patterns, we turn to econometric analysis and run the following cross-country panel regression:

$$RCO_{c,t+h} = \alpha_{1,h}\Delta(C/Y)_{c,t} + \alpha_{2,h}FCI_{c,t} + \alpha_{3,h}\,Real\ GDP\ Growth_{c,t} + \mu_{c,h} + \mu_{t,h} + \varepsilon_{c,t+h} \tag{2}$$

where $RCO_{c,t+h}$ is the riskiness of credit origin in country c in year $t+h$ $(h=0,1)$; $\Delta(C/Y)_{c,t}$ is the annual change in the credit-to-GDP ratio at time t, $FCI_{c,t}$ denotes the financial condition index (a higher value indicates looser financial conditions), $Real\ GDP\ Growth_{c,t}$ is the annual real GDP growth rate and $\mu_{c,h}$ and $\mu_{t,h}$ are country and year fixed effects, respectively. Standard errors are clustered at the country level.

Table 2, Panel A presents our baseline results. Greater expansions in credit are associated with a statistically significant higher RCO both contemporaneously and one year ahead, indicating that these expansions coincide with riskier banks growing their loan portfolio relatively faster. The coefficients are larger and more significant for the forward relationship (h=1; columns (2) and (4)), indicating that the credit expansion leads risk-taking as measured by RCO. Quantitatively, the results in column (2), indicate that an increase in the credit-to-GDP ratio by one standard deviation (4.9 percentage points) is associated with an increase in RCO by 0.2 standard deviations (a value of 0.26) one year ahead. Thus, there is a statistically significant relationship between RCO and aggregate credit expansions, but its magnitude is not large. RCO is a feature of the credit cycle but is not purely driven by it. The regression coefficients for the size of the credit expansion decline in magnitude and significance when including year fixed effects in the specifications (columns (3) and (4)), which indicates that part of its explanatory power comes from global cycles, as suggested by Figure 1.

Buoyant domestic financial conditions are positively related to contemporaneous and future RCO, although the relationship is statistically significant only when the specification excludes year fixed effects. Quantitatively, FCI's relationship with RCO is also somewhat weaker than that of credit expansions. A one standard deviation increase in FCI is associated with a 0.1 standard deviation increase in RCO (0.1–0.15). Regressions augmented by the interaction between the size of credit expansion and financial conditions do not yield significant results for the interaction coefficient, with all other results remaining unaltered (unreported results).

There is no contemporaneous or lagged relationship between RCO and the business cycle, as captured by the regression coefficient on real GDP growth, as this coefficient is not statistically significant in any specification.

We next document the robustness of these findings to several perturbations in the remainder of Table 2. Panel B reports the results obtained with our restricted sample (that includes only country-years with at least 20 banks with 5 years of data, versus at least 10 banks considered in the baseline). Panel C shows results for the alternative RCO measure based on the synthetic EDF bank riskiness measure. Regressions underlying Panel D include the change in the current-account-to-GDP ratio, inflation, and the change in the bilateral exchange rate vis-à-vis the U.S. dollar as macro controls. Overall, the conclusions are similar to those obtained for the baseline specifications. The relationship between RCO and credit expansions is positive and almost always (11 out of 12) statistically significant at conventional levels. The relationship with FCI is almost always positive but only sometimes significant (3 cases out of 12) and its significance disappears with the inclusion of year fixed effects. The relationship with real GDP growth is statistically significant in only one specification without year fixed effects.

Overall, these results show that, at the country level, periods of larger credit expansions are associated with a relatively higher RCO. We check whether this relationship between bank riskiness, bank lending activity, and aggregate credit developments is also present at the micro level by estimating the coefficients of the following equation:

$$G_{i,c,t} = \beta G_{i,c,t-1} + \gamma_1 Riskiness_{i,c,t-1} + \gamma_2 Riskiness_{i,c,t-1} \times Cycle_{c,t} + \gamma_3{}' X_{i,c,t-1} + \theta_i + \mu_{c,t} + \varepsilon_{i,c,t} \qquad (3)$$

where $G_{i,c,t}$ is a variable capturing the annual growth rate of the size of bank i from country *c* between years *t-1* and *t*. Our main focus is on total loan growth, but we also explore the growth rate of total assets, total debt, and total equity.[13] To be consistent with our definition of RCO, the variable $Risk_{i,c,t-1}$ is the within country-year decile of the first lag of our baseline bank riskiness indicator (minus z-score). $Cycle_{c,t}$ is the size of the aggregate credit expansion (the annual change in the credit-to-GDP ratio). $X_{i,c,t-1}$ is a set of bank-level controls which includes the liquid asset ratio and bank loan market share (to capture size in the loan market). θ_i and $\mu_{c,t}$

[13] Total debt is defined as total assets less total equity.

correspond to bank and country-year fixed effects respectively. Standard errors are clustered at the bank level. Except for $Risk_{i,c,t-1}$, all bank-level variables are winsorized at the 0.5 percent level.

Table 3 presents our findings. The estimates show that a riskier bank expands its loan portfolio more slowly than a safer one on average over the cycle and that this difference varies with the state of the cycle (column (1)). The effect of bank risk shrinks— that is, it becomes less negative— when the aggregate credit expansion is stronger. A one-standard-deviation increase in the credit-to-GDP ratio is associated with relatively faster annual lending growth by 1.1 percentage points for a bank at the second decile of the z-score distribution relative to a bank at the 8th decile of the z-score distribution.

The pattern is similar for the expansion in total assets or total debt. The growth of assets and debt of a riskier bank is relatively faster during larger credit expansions (columns (2) and (3)). However, there is no such pattern for the growth in total equity (column (4)). Overall, these findings indicate that bank riskiness heterogeneity tends to drive the bank credit cycle.

As for the country-level regressions, we also check whether our results are results are robust to the choice of sample or bank riskiness measure. Panel B of Table 3 presents the key coefficient for the interaction of bank riskiness and size of credit expansion for various specifications that use our alternative samples, as well as the synthetic EDF riskiness indicator. All results are similar to those reported for the baseline case.

Overall, these results indicate a sizable degree of procyclicality of RCO with respect to aggregate credit expansions, and a weaker relationship with financial conditions. They provide a new stylized fact on the credit cycle and help shed additional light on why large expansions of credit are often followed by adverse macrofinancial outcomes. Not only do such expansions increase leverage in the financial and nonfinancial sectors, making the economy more vulnerable to adverse shocks, as is commonly emphasized in the literature, but they also tend to rely on relatively riskier banks. In other words, the aggregate build-up in vulnerabilities during large credit expansions has an important compositional dimension.

IV. Riskiness Of Credit Origins and Downside Risks to Growth

Having established that the distribution of the sources of credit turns riskier during periods of large credit expansions, we analyze whether RCO helps predict the distribution of future GDP growth controlling for the change in the credit-to-GDP ratio and financial conditions. We conjecture that, other things equal, a relatively larger expansion of credit by riskier banks would result in a financial system that is more vulnerable to shocks and would further amplify the impact of these shocks on the real economy.

To investigate this hypothesis, we study the relationship between RCO and various percentiles of the future GDP growth distribution by estimating the parameters of a series of panel quantile regression for various percentiles τ of the 1 to 3-year-ahead average cumulative GDP growth distributions:

$$Q(\tau, \Delta y_{c,t,h}) = \alpha_{1,h}(\tau)\Delta\left(\frac{Credit}{GDP}\right)_{c,t}^{mv3} + \alpha_{2,h}(\tau)FCI_{c,t}^{mv3} + \alpha_{3,h}(\tau)RCO_{c,t}^{mv3} + \alpha_{4,h}(\tau)'X_{c,t}^{mv3} + \mu_{c,h}(\tau) + \varepsilon_{c,t,h}\,, \quad (4)$$

where $\Delta y_{c,t,h}$ is average cumulative real GDP growth rate of country c from year *t* to year *t*+*h*, where *h*=1, 2, 3. The change in the credit-to-GDP ratio, FCI, and RCO are the same as in the previous section. In our baseline specification, the set of controls (*X*) includes real GDP growth and global financial conditions (defined as the average of FCI across all countries in our sample). Other specifications extend the set of controls to include the aggregate z-score (to capture aggregate resilience), the change in the ratio of current-account-to-GDP (following Jorda et al. 2011), measures of the global financial cycle, namely the (log of) VIX and the (log of) dollar index (DXY), and the interaction of the change in the credit-to-GDP ratio and the financial conditions index.[14] The function $Q(\tau, x)$ denotes percentile τ of variable x. Following the literature (Mian et al. 2017; Brandao-Marques et al. 2022, among others), all explanatory variables enter the equation as their three-year moving average (*mv3* superscript).[15]

We estimate Equation (4) for $\tau \in \{20, 50, 80\}$, that is, the twentieth, the fiftieth, and the eightieth percentile of the future cumulative GDP growth distribution. In (4), the dependence on τ of the coefficients captures the fact that they can vary across these percentiles. We place a particular focus on the twentieth percentile to assess how RCO relates to downside risks to growth, and we refer to this model as “growth-at-risk” (Adrian et al., 2022). We estimate the equation coefficients using Canay (2011)’s method which assumes that the country fixed effects are common across percentiles (i.e. $\alpha_{c,h}(\tau) = \alpha_{c,h}$ for each τ), but check the robustness of our findings to using Machado and Santos-Silva (2019)’s method which allows the country fixed effects to also vary across percentiles—at the expense of somewhat restrictive assumptions regarding heteroscedasticity and larger standard errors.[16] The methods available for the estimation of this class of non-linear models do not allow for the inclusion of time fixed effects, which makes it especially important to check the robustness of the results to the inclusion of global variables that the literature has used to capture the state of the global financial cycle.

The estimated coefficients for the twentieth, the fiftieth, and the eightieth percentiles at horizons from one to three years ahead reveal that a greater RCO shifts the left tail and, to a lesser extent, the median of the one-year ahead growth distribution to the left (Table 4, columns 1-3). In other words, the RCO has a significant predictive power for future downside risks to growth.[17] The leftward shift of the growth distribution remains significant two- and three-year into the future and extends even to the right tail of the distributions at the three-year horizon (columns 4-9). The coefficients for the twentieth and the fiftieth percentiles increase between $h = 1$ and $h = 2$. A one-standard-deviation increase in RCO moves the left tail of the two-year ahead average

[14] The latter controls for the possibility that it is the combination of easy financial conditions and credit growth that is particularly harmful for future economic performance (Krishnamurthy and Muir, 2017)

[15] We compute the three-year moving average of a variable Xat time t as $\frac{1}{3}(X_t + X_{t-1} + X_{t-2})$.

[16] Additional results obtained using Koenker (2004)’s penalized fixed-effects methods are similar to those reported using Canay (2011)’s method, and those obtained using Powell (2016)’s non-additive fixed effects method display stronger significance when modified to allow for locational shifts in the country-distributions by de-meaning the variables.

[17] We also ran a specification that also includes the interaction between RCO and the change in the credit-to-GDP ratio to analyze whether the predictive power of RCO was stronger when the size of the credit expansion is larger. The coefficient of this interaction term turned out to be insignificant.

annual real GDP growth distribution by 31 basis points, which is sizeable. In line with the existing literature, we find that stronger credit growth hurts future downside risks to GDP growth (regardless of the percentile of the distribution). Looser global financial conditions also lead to leftward shift in the future GDP growth distributions, especially in the low quantile, while looser domestic financial conditions shift them rightward.

Adding other controls does not significantly alter the predictive power of RCO for future downside risks to growth. Panel A of Table 5 presents the results of specifications including the full set of macro controls. At the 2-year and 3-year horizons, the coefficient for RCO remains negative for all quantiles. It is statistically significant and has the greatest magnitude at the twentieth percentile.

Panel B of Table 5 documents the robustness of the main findings in our baseline specifications to changes in the estimation method, the sample, and the measure of bank riskiness. It reports the coefficient of RCO for the three percentiles (the twentieth, the fiftieth, and the eightieth) of interest and three different horizons (1, 2, and 3 years ahead) when using the estimation method of Machado and Santos-Silva (2017) (row (a)), our restricted sample (row (b)), and RCO based on the synthetic EDF measure of riskiness (row (c)). The coefficient for the twentieth percentile is negative at all horizons and significant at two and three years ahead, indicating the robustness of our key finding. Similarly, all the coefficients for the fiftieth percentile quantile regressions are negative, and most are statistically significant at the 2-year and 3-year horizons.

Overall, these findings clearly show that a greater RCO is bad news for future downside risks to economic activity.

V. Why Does RCO Predict Downside risks? Exploring the Channels

The previous two sections presented evidence that the RCO increases during periods of aggregate credit expansion and that RCO also helps predict downside risks to GDP growth even after controlling for the size of the credit expansion and a range of other factors.

As discussed earlier in the introduction, RCO could help predict future economic activity through three broad channels. First, if riskier banks have a greater propensity to lend to riskier borrowers when their loan portfolio grows relatively faster, RCO could be related to a riskier allocation of credit and a weakening of the future quality of the aggregate loan portfolio (asset quality channel). Second, a high RCO could capture a buoyant sentiment, either in the banking sector or in financial markets at large (sentiment channel). Third, changes in RCO could capture variations in the concentration of an economy’s loan portfolio in riskier banks, which are by definition the least resilient banks. To the extent that these banks are more likely to reduce their lending in response to a future adverse shock, and that borrowers face frictions when trying to shift lenders, this could result in an aggregate contraction in lending and activity (resilience channels). This section explores these three potential channels sequentially.

Asset Quality Channel

To check for the relevance of this channel, we test whether riskier banks lend to relatively riskier borrowers when expanding their loan portfolio relatively faster. We consider both ex-post and ex-ante measures of the riskiness of a bank's portfolio. We begin by exploring ex-post measures, namely a bank's future flow of loan loss provisions and future change in nonperforming loan ratio. We thus estimate the following two sets of local-projections regressions:

$$LLP_{i,c,t,h} = \beta_h LLP_{i,c,t-1} + \gamma_{1,h} HLG_{i,c,t} + \gamma_{2,h} Riskiness_{i,c,t-1} + \gamma_{3,h} Riskiness_{i,c,t-1} \times HLG_{i,c,t} + \gamma_{4,h}{}' X_{i,c,t-1} + \theta_{i,c,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h} \quad (5)$$

$$DNPL_{i,c,t,h} = \beta_h DNPL_{i,c,t-1} + \gamma_{1,h} HLG_{i,c,t} + \gamma_{2,h} Riskiness_{i,c,t-1} + \gamma_{3,h} Riskiness_{i,c,t-1} \times HLG_{i,c,t} + \gamma_{4,h}{}' X_{i,c,t-1} + \theta_{i,c,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h} \quad (6)$$

where $LLP_{i,c,t,h}$ is the average of the flow of loan-loss provisions of bank i in country c during years t to $t+h$ ($h = 1,2,3$) as a ratio to gross loans at time $t-1$ and $DNPL_{i,c,t,h}$ is the average change in the stock of nonperforming loans between years t and $t+h$ divided by lagged gross loans. $Riskiness_{i,c,t-1}$ is the within-country-year decile of the first lag of the bank-level riskiness indicator, and $HLG_{i,c,t}$ is a dummy that takes the value 1 if the loan growth of bank i from country c in year t is above the median across banks in that country-year. The vector $X_{i,c,t-1}$ includes two controls (bank loan market share and liquidity) as in Equation (3), while $\mu_{c,t,h}$ and $\theta_{i,c,h}$ denote country-year and bank fixed effects capturing common shocks affecting all banks in a country and unobservable bank characteristics, respectively. In these regressions, both the average flow of loan loss provisions and change in NPLs are expressed in basis points.

The results obtained for these regressions, reported in Table 6 show that banks that grow their loan book relatively faster suffer a deterioration in the flow of loan loss provisions down the road (columns (1)-(3)). This result echoes Fahlenbrach et al. (2018) which provides similar evidence for banks in the United States. Furthermore, and more importantly for our analysis, this deterioration is stronger when the bank is an ex-ante riskier bank as shown by the positive and significant coefficient for the interaction term. We reach similar conclusions when we assess the quality of banks' loan portfolios using the cumulative change in the NPL ratio (columns (4)-(6)). Regardless of the measure of performance, the coefficients for the interaction term are significant for all three-time horizons considered.[18]

To study whether the relationship between bank riskiness and borrower riskiness documented above extends to ex-ante measures of riskiness, we exploit syndicated loans data. Information on data sources and dataset construction for this specific analysis is provided in Appendix 3. For each bank in our sample that participates in the syndicated loan market, we compute the share of its syndicated lending origination that goes to loans classified as leveraged or highly leveraged in a year. We label this variable Leveraged Loan Share (LLS). While this is a good measure of the extent to which a bank lends to risky borrowers in a particular loan market from

[18] Findings for the restricted bank sample are very robust regardless of the metric of bank performance. Results for the alternative bank riskiness measure are very strong for the cumulative change in NPLs but less significant in the case of the flow of loan loss provisions. Results are available upon request.

an ex-ante perspective, it can be computed only for a small sample of banks (those that participate in the syndicated loans market).[19] We analyze its relationship to bank riskiness and loan portfolio growth using the following local projections regression:

$$LLS_{i,c,t,h} = \gamma_{1,h}HLG_{i,c,t} + \gamma_{2,h}Riskiness_{i,c,t-1} + \gamma_{3h}Riskiness_{i,c,t-1} \times HLG_{i,c,t} + \gamma_{4h}{}'X_{i,c,t-1} + \theta_{i,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h} \tag{7}$$

The results, reported in columns (7)-(9) of Table 6, show that, while riskier banks have a relatively lower LLS when their portfolio growth is relatively low, the sign of this relationship reverses when it is relatively high. This relatively stronger risk-taking occurs up to 2 years ahead. While a caveat is in order because of the smaller bank sample size, these findings point in the same direction and confirm those obtained with ex-post measures of risk-taking.

Having established the validity of the channel at the micro level, we turn again to our growth-at-risk setup to test whether this channel can account for the explanatory power of RCO at the macro level by adding a direct aggregate measure of the riskiness of borrowers to the regression specification. The measure we use is the RCA from Brandao et al. (2022). This measure is constructed using a similar logic as RCO and captures the extent to which more leveraged borrowers are expanding their debt relatively faster. We include RCA in the regression in the same manner as RCO, that is as a three-year moving average. Table 7 presents results of panel quantile regressions for the twentieth percentile for three-time horizons (h=1,2,3). For each time horizon, the first column corresponds to a regression with RCA only, the second column to a regression with RCO only, and the third column to a regression with both RCA and RCO included. While both RCA and RCO are significant at horizons up to two years when entering separately, controlling for RCA renders insignificant the coefficients for RCO at 1 year horizon, and decreases its size at longer horizons without affecting its significance. Thus, while the micro evidence indicates the validity of the asset quality channel, an aggregate proxy for asset quality at the macro level does not make RCO clearly less significant as a predictor of downside risks to growth. This indicates that RCO is a better aggregate proxy for asset quality or that other channels are at play.

[19] Also, information on whether banks retain these loans on their balance sheets or sell them after origination is not publicly available.

Sentiment Channel

We next explore the possibility that RCO could capture banking sector sentiment or investor sentiment. In the spirit of Lopez-Salido et al (2017) who call credit sentiment a financial variable that helps predict future changes in credit spreads, we call banking sector sentiment a financial variable that helps predict future changes in bank lending standards and investor sentiment a financial variable that helps predict future changes in financial conditions.

We gather cross-country data on quarterly changes in bank lending standards (BLS) from bank loan officers surveys. The surveys measure the difference between the fraction of officers that declared having tightened their lending standards and those that declared having loosened them.[20] These data are available for a subsample of 31 countries and for a shorter timespan than RCO (there is more than five countries with data only after 2003). This reduces the sample size by about half, so the results below must be interpreted with care.

We analyze the relationship between RCO and banking sector sentiment using the following local projections regression:

$$BLS_{c,t+h} = \alpha_{1,h} BLS_{c,t} + \alpha_{2,h} RCO_{c,t}^{mv3} + \mu_{c,h} + \mu_{t,h} + \varepsilon_{c,t,h} \tag{8}$$

where $BLS_{c,t}$ is the change in bank lending standards in country c in year t and the rest of the notation is as in Equation (4). The $\mu_{c,h}$ and $\mu_{t,h}$ coefficients are country and year fixed effects, respectively. The results are presented in Table 8 for three time horizons (h=1,2,3). For each time horizon, the first column shows results of a specification with RCO only, the second column shows results of a specification with BLS only, and the third column provides results of a specification with both RCO and BLS included. A higher RCO helps predict future tightening in lending standards at horizons of 1 to 2 years ahead, including when current bank lending standards are controlled for (columns (7)-(9)). This indicates that RCO's predictive power for downside risks to growth may come from its ability to predict future banking sector sentiment.

We then examine the relationship between RCO and investor sentiment using a similar local projections regression:

$$\Delta FCI_{c,t+h} = \alpha_{1,h} FCI_{c,t}^{mv3} + \alpha_{2,h} RCO_{c,t}^{mv3} + \mu_{c,h} + \mu_{t,h} + \varepsilon_{c,t,h} \tag{9}$$

where $\Delta FCI_{c,t+h}$ is the change in bank lending standards in country c in year $t+h$ and the rest of the notation is as in Equation (8). The results are presented in Table 9 for three-time horizons (h=1,2,3). Again, for each time horizon, the first column shows results of a specification with RCO only, the second column shows results of a specification with FCI only, and the third column provides results of a specification with both RCO and FCI included. A higher RCO helps predict future tightening in financial conditions at 1 and 2 years ahead, but when concurrent financial conditions are controlled for (columns (7)-(9)) this predictive power appears only at the two-year horizon. This result aligns with the sentiment channel of RCO. A further confirmation of this channel is

[20] We collapse the quarterly measure to an annual frequency by taking its simple average and standardize the variable within a year to account for idiosyncratic differences in the manner the surveys are conducted.

provided by the results of a set of growth-at-risk regressions where the set of explanatory variables is enriched by the change in financial conditions at t+1. As shown in Table 10, the inclusion of this term reduces the magnitude of the RCO coefficient and eliminates its significance at horizons of up to two years.

Resilience Channel

We finally turn to the exploration of the resilience channel. We check whether this channel could account for RCO's predictive power for downside risks to growth by first exploring the relationship between RCO and future banking sector stock returns. Arguably, if RCO predicts future downside risks to growth because if captures a form of banking sector fragility, it must also predict downside risks to banking sector financial performance. We thus run the following panel quantile regressions:

$$Q\left(\tau, r_{c,t,h}\right) = \alpha_{1,h}(\tau)\Delta\left(\frac{Credit}{GDP}\right)_{c,t}^{mv3} + \alpha_{2,h}(\tau)FCI_{c,t}^{mv3} + \alpha_{3,h}(\tau)RCO_{c,t}^{mv3} + \alpha_{4,h}(\tau)'X_{c,t}^{mv3} + \mu_{c,h}(\tau) + \varepsilon_{c,t,h}\ , \quad (10)$$

where $r_{c,t,h}$ is the h-year-ahead (h=1,2,3) cumulative return of country c at time t, and the rest of the notation is as in Equation (4). We focus on the same three quantiles as before (the twentieth, the fiftieth, and the eightieth percentiles) as well as the tenth percentile, to be able to capture the very left tail of the distribution. Panel A of Table 11 reports results of the baseline specification that includes only RCO, $\Delta\left(\frac{Credit}{GDP}\right)$, FCI and the fixed effects as explanatory variables, while Panel B of the same table reports results including the full set of macro controls described in Panel A of Table 6. These results show that while RCO generally predicts adverse banking sector stock return performance, it does so significantly mostly for the tenth percentile of the distribution at horizons of up to two years. In the baseline, a one-decile increase in RCO predicts a shift in the very left tail of the one-year-ahead stock return distribution by about 480 basis points.

We then test whether riskier banks (which are also less resilient by definition) are more likely to reduce future lending, both on average across time and following large adverse financial shocks. To this end, we estimate the parameters of the following bank-level local projections regression:

$$\begin{aligned} LG_{i,c,t,h} = \beta_h HLG_{i,c,t} + \gamma_{1,h} Riskiness_{i,c,t-1} + \gamma_{2,h} HLG_{i,c,t} \times Crisis_{c,t+h} \\ + \gamma_{3,h} Riskiness_{i,c,t-1} \times Crisis_{c,t+h} + \theta_{i,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h}\ , \quad (11) \end{aligned}$$

where $LG_{i,c,t,h}$ is the average cumulative growth of gross loans of bank i from country c between years t and $t+h$, $Crisis_{c,t+h}$ is a dummy that takes the value 1 if country c experiences a systemic banking crisis in year $t+h$, and the rest of the notation is the same as in Equation (5). We explore time horizons up to four years (h=1,2,3,4). The systemic banking crisis data are sourced from Laeven and Valencia (2020).

The results are presented in Table 12 and show that riskier banks tend to exhibit lower rates of future loan growth, especially at shorter horizons (columns (1)-(4)). Furthermore, the relatively lower growth rates of riskier banks are especially pronounced during periods of large adverse financial shocks, as captured by the occurrence of systemic financial crises (columns (5)-(8)). A one-decile-increase in $Riskiness$ is associated with a deterioration in gross loan growth performance of 0.45 percentage points if a crisis hits the following year.

This deterioration is present at longer horizons too, although its magnitude is about half.[21] Therefore, a relatively greater concentration of the aggregate loan portfolio in riskier (i.e., less resilient) banks during periods when RCO increases could hurt future aggregate credit growth after a large adverse shock.

We then check whether this resilience channel could account for the significance of RCO in the growth-at-risk regressions by augmenting Equation (4) with two other aggregate fragility indicators, namely the average riskiness (i.e. the negative of the average z-score) measure across banks (which is part of our set of "additional" controls in Section IV), and the skewness of the asset-weighted leverage distribution (constructed as in Coimbra and Rey 2018). For each of the three-time horizons (h=1,2,3), we examined regression results (for the twentieth percentile) of a first specification that includes these 2 indicators, a second specification that includes RCO, and a third one that includes both (see Table 13). While the coefficient for average riskiness is always significant and indicates that a higher aggregate z-score is a source of resilience, the asset-weighted leverage skewness does not seem to have a particularly strong relationship with the left tail of the future growth distribution.[22] Turning to the RCO regression coefficient, we find that its magnitude declines by about 20 percent at the 1-year and 3-year horizons when controlling for the other two resilience fragility indicators, suggesting the presence of a resilience channel in the aggregate.

Overall, the results suggest that part of the explanatory power of RCO comes from its relationship with a concentration of lending in riskier banks that are more prone to cut future lending, especially after adverse shocks. Nonetheless, this channel does not exhaust the information about future downside risks to activity contained in RCO.

VI. Conclusion

Many empirical studies have explored how the size of credit expansions drives future macroeconomic outcomes and have documented that fast expansions often lead to financial crises and higher downside risks to GDP growth. In this paper, we enrich this literature by focusing on the role of the composition of credit across heterogeneous banks. We construct a new measure of the RCO capturing the extent to which aggregate credit growth is driven by relatively riskier banks. We establish the procyclicality of this measure and thus uncover a new dimension of the credit cycle. More importantly, we also show that the quality of the credit expansion as measured by RCO helps predict future macroeconomic outcomes after controlling for size of credit expansion and financial conditions.

We also present evidence of three inter-related channels that likely drive this latter result. First, the expansion in the loan portfolio of riskier banks when they grow relatively faster seems to target riskier borrowers, which has adverse implications for their asset quality. Second, RCO helps predict future changes in bank lending standards and financial conditions, suggesting that it is also a measure of sentiment. Third, because riskier banks tend to cut back on lending relatively more during periods of large adverse financial shocks, the banking

[21] The results also show that loan growth rates are serially correlated as top lenders keep growing faster for the subsequent two years, and eventually revert to the mean as top lenders have lower loan growth rates after 3 years.

[22] The latter is, however, negatively related to future median GDP growth at the three-year horizon (unreported result).

sector's aggregate lending capacity is less resilient following periods when these banks have expanded relatively more.

Our paper complements recent work by Brandao-Marques et al. (2022) which documented the importance of accounting for the RCA in predicting financial crises and downside risks to growth. Our findings highlight the importance of accounting not only for borrower heterogeneity but also for lender heterogeneity in empirical and theoretical models of the credit cycle, echoing recent work by Coimbra and Rey (2023). We believe our findings to be also relevant for prudential authorities as they establish a new link between micro- and macro-prudential approaches and call for accounting of lender heterogeneity is the calibration of macroprudential capital buffers. Future research based on more granular dataset could shed further light on the mechanisms through which RCO matters for downside risks to economic activity, including by analyzing how the matching of lender and borrower quality varies over the credit cycle.

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Table 1. Summary Statistics

A. Bank-Level Variables

Overall (bank-year)	Z-score (percent)	Synth EDF (no units)	Loan Growth (percent)	LLP (percent)	NPL (percent)	Δ(NPL) (percent)
Mean	147	0.00	7.82	1.02	4.43	0.21
Standard Deviation	252	0.30	16.96	1.67	5.40	2.05
Median	59	0.00	6.40	0.49	2.51	0.02
25th percentile	144	-0.14	-0.97	0.13	0.97	-0.33
75th percentile	25	0.14	15.67	1.20	5.66	0.55
Number of observations	39,730	41,085	43,091	44,515	32,004	30,298

B. Country-Level Variables

Overall (country-year)	RCO (z-score) (deciles)	RCO (synt. EDF) (deciles)	Δ(Credit/GDP) (percent)	FCI	GDP growth (percent)	CA/GDP (percent)
Mean	0.0	0.0	1.1	0.0	3.1	0.1
Standard Deviation	1.3	1.4	4.9	1.0	3.6	2.5
Median	0.0	0.0	1.0	0.1	3.0	0.0
25th percentile	-0.8	-0.9	-1.2	-0.5	1.4	-0.9
75th percentile	0.8	0.9	3.2	0.7	5.1	0.9
Number of observations	833	855	1,280	1,320	1,310	1,303

The table reports summary statistics for key bank and country level variables used in the paper. Z-score is the sum of a bank's return on average assets and leverage ratio, divided by the historical (three-year) standard deviation of its returns on average assets. Synth-EDF is a synthetic measure of bank riskiness obtained from regressing banks' EDF on banks' fundamentals. Loan Growth is the annual growth rate of a bank's gross loans. LLP is the ratio of a bank's loan loss provisions to its lagged gross loans. NPL is the ratio of a bank's nonperforming loans to its lagged gross loans and DNPL is the change in NPL between t and t-1, divided by lagged (t-1) gross loans. RCO (z-score) and RCO (synth EDF) are the country level indicators of the riskiness of credit RCO GDP. FCI is the financial conditions index, built as described in the Appendix 3. GDP growth is the annual rate of growth of real GDP, and CA/GDP is the ratio of the current account to GDP.

Table 2. RCO Cyclicality

	A. Baseline				B. Restricted sample			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	h=0	h=1	h=0	h=1	h=0	h=1	h=0	h=1
Real GDP Growth	-0.025	-0.013	-0.027	-0.028	-0.003	-0.003	-0.015	-0.015
	(0.033)	(0.023)	(0.042)	(0.028)	(0.041)	(0.028)	(0.051)	(0.032)
Δ(Credit/GDP)	0.029*	0.051***	0.020	0.043**	0.025*	0.036**	0.025*	0.030*
	(0.016)	(0.017)	(0.017)	(0.019)	(0.013)	(0.013)	(0.014)	(0.015)
FCI	0.096*	0.146**	0.166	0.241	0.070	0.145**	-0.001	0.127
	(0.056)	(0.065)	(0.178)	(0.164)	(0.058)	(0.069)	(0.174)	(0.174)
Observations	825	771	825	771	648	611	648	611
No. countries	41	41	41	41	33	33	33	33
R-squared	0.015	0.043	0.046	0.073	0.013	0.037	0.051	0.068
Adjusted R2	0.011	0.039	0.011	0.038	0.008	0.032	0.007	0.023
Macro Controls	✗	✗	✗	✗	✗	✗	✗	✗
Year FE	✗	✗	✓	✓	✗	✗	✓	✓

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	C. Alternative RCO measure				D. Adding macro controls			
	h=0	h=1	h=0	h=1	h=0	h=1	h=0	h=1
Real GDP Growth	0.006	0.050**	-0.041	0.044	-0.012	0.001	0.013	0.000
	(0.034)	(0.024)	(0.041)	(0.033)	(0.028)	(0.023)	(0.034)	(0.027)
Δ(Credit/GDP)	0.030**	0.050***	0.025*	0.040*	0.029*	0.052***	0.018	0.043**
	(0.014)	(0.016)	(0.014)	(0.021)	(0.017)	(0.018)	(0.019)	(0.020)
FCI	-0.032	0.054	-0.123	0.001	0.140**	0.154**	0.260	0.278
	(0.071)	(0.075)	(0.131)	(0.169)	(0.058)	(0.064)	(0.185)	(0.166)
Observations	648	613	648	613	821	767	821	767
No. countries	33	33	33	33	41	41	41	41
R-squared	0.012	0.053	0.080	0.094	0.050	0.048	0.085	0.080
Adjusted R2	0.008	0.049	0.035	0.049	0.043	0.041	0.048	0.041
Macro Controls	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✗	✗	✓	✓	✗	✗	✓	✓

The table reports OLS regressions of the contemporaneous (h=0) or one period forward (h=1) relationship between the RCO and D, the dependent variable is the z-score-based measure of RCO, while panel C uses the measure based on the synthetic EDF indicator. Panels A, C, and D report regressions using the baseline sample. Panel B uses the restricted sample that requires that a country-year has at least 20 eligible banks to be included. Panel D expands the set of macro controls adding the change in current-account-to-GDP ratio, inflation, and the change in the bilateral exchange rate vis-à-vis the U.S. dollar as macro controls. Real GDP growth is the annual rate of growth of real GDP, Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. FCI is the financial conditions index, built as described in the Appendix 3. All regressions include country fixed effects. Standard errors clustered at the country level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 3. RCO Cyclicality: Bank Level Evidence

	(1)	(2)	(3)	(4)
	Loan Growth	Asset Growth	Debt Growth	Equity Growth
A. Baseline				
Riskiness	-0.348***	-0.379***	-0.459***	0.279***
	(0.035)	(0.034)	(0.039)	(0.044)
Riskiness X Δ(Credit/GDP)	0.047***	0.038***	0.034***	0.001
	(0.009)	(0.009)	(0.010)	(0.012)
Lagged Dependent Variable	0.129***	0.048***	0.017	-0.066***
	(0.011)	(0.012)	(0.012)	(0.010)
Observations	29,700	29,700	27,353	27,353
R-squared	0.506	0.474	0.460	0.361
Country-Year FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
B. Alternative Bank Riskiness Measure and Sample				
(a) Synthetic EDF	0.039***	0.028***	0.032***	0.005
	(0.010)	(0.009)	(0.009)	(0.012)
(b) Restricted Sample	0.042***	0.038***	0.034***	0.005
	(0.010)	(0.010)	(0.012)	(0.012)

The table reports the coefficients of bank-level OLS regressions between the dependent variables shown in each column and the explanatory variables listed in the columns. Loan Growth, Asset Growth, Debt Growth, and Equity Growth are the annual growth rate of a bank´s gross loans, total assets, total debt (total assets minus total equity), and total equity, respectively. Riskiness is the bank-level measure of riskiness, which in all these regressions corresponds to a bank´s z-score, which is the sum of a bank's return on average assets and leverage ratio, divided by the historical (three-year) standard deviation of its returns on average assets. Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. Lagged dependent variable corresponds to the one-year lagged value of the dependent variable, included to control for convergence effects. Panel B reports results for alternative measures of RCO and sample. Only the coefficient for the interaction of Riskiness X Δ(Credit/GDP) is reported for space reasons. In Row (a) Riskiness is the synthetic EDF indicator and Row (b) uses the baseline z-score indicator but relies on the restricted sample that requires that a country-year has at least 20 eligible banks to be included. Standard errors are clustered at the bank level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 4. RCO and Growth-at-Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
	τ=20	τ=50	τ=80	τ=20	τ=50	τ=80	τ=20	τ=50	τ=80
Real GDP Growth	0.349***	0.317***	0.406***	0.166*	0.245***	0.322***	0.173**	0.147***	0.221***
	(0.085)	(0.074)	(0.070)	(0.086)	(0.052)	(0.080)	(0.069)	(0.051)	(0.080)
Δ(Credit/GDP)	-0.116***	-0.044*	0.010	-0.121***	-0.077***	-0.038	-0.128***	-0.118***	-0.098***
	(0.026)	(0.023)	(0.026)	(0.023)	(0.021)	(0.027)	(0.020)	(0.025)	(0.027)
FCI	0.441*	0.323*	-0.075	0.768***	0.254*	-0.009	0.440**	0.535***	0.269
	(0.265)	(0.167)	(0.195)	(0.207)	(0.143)	(0.168)	(0.194)	(0.141)	(0.186)
Global FCI	-0.352	-0.640***	-0.317	-1.052***	-0.576***	-0.311	-0.960***	-0.900***	-0.647**
	(0.282)	(0.200)	(0.263)	(0.226)	(0.186)	(0.250)	(0.211)	(0.184)	(0.251)
RCO	-0.186*	-0.082	-0.032	-0.311***	-0.155**	-0.090	-0.278***	-0.173**	-0.171**
	(0.099)	(0.084)	(0.095)	(0.091)	(0.076)	(0.084)	(0.062)	(0.075)	(0.074)
Observations	678	678	678	642	642	642	604	604	604

The table reports quantile regressions of the one to three-year forward (h=1, 2, 3) relationship between Real GDP Growth (the dependent variable) and the (t=0) RCO, controlling for a series of macro variables. For each horizon h, the 3 columns reported show the coefficients of quantile regressions for the twentieth, the fiftieth, and the eightieth percentile using the Canay (2011) method for panel quantile regressions (with bootstrapped standard errors). Explanatory variables enter the regression as the lag of their simple three-year moving average. Real GDP growth is the annual rate of growth of real GDP, Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. FCI is the financial conditions index, built as described in the Appendix 3 and Global FCI is the world average of this index. RCO corresponds to the z-score based measure of the riskiness of credit origins. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 5. RCO and Growth at Risk: Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
	Q=20	Q=50	Q=80	Q=20	Q=50	Q=80	Q=20	Q=50	Q=80
A. Additional Macro Controls									
Real GDP Growth	0.363***	0.340***	0.431***	0.219**	0.327***	0.398***	0.167***	0.190***	0.265***
	(0.093)	(0.071)	(0.080)	(0.087)	(0.060)	(0.099)	(0.064)	(0.059)	(0.071)
Δ[Credit/GDP]	-0.109***	-0.034	0.026	-0.140***	-0.078***	-0.013	-0.161***	-0.108***	-0.067**
	(0.038)	(0.022)	(0.024)	(0.022)	(0.020)	(0.024)	(0.025)	(0.023)	(0.029)
FCI	0.439*	0.329**	-0.112	0.387**	0.284**	0.008	0.481***	0.380***	0.204
	(0.237)	(0.140)	(0.176)	(0.194)	(0.128)	(0.195)	(0.171)	(0.127)	(0.161)
Global FCI	-2.038***	-1.971***	-0.422	-2.823***	-2.221***	-1.049**	-2.917***	-2.202***	-2.096***
	(0.546)	(0.396)	(0.671)	(0.607)	(0.323)	(0.492)	(0.414)	(0.336)	(0.513)
CA/GDP	0.143	0.103	0.240**	-0.004	0.101	0.265***	0.006	0.085	0.256***
	(0.121)	(0.083)	(0.095)	(0.101)	(0.065)	(0.089)	(0.102)	(0.065)	(0.085)
VIX	-4.914***	-3.741***	-0.502	-5.405***	-4.378***	-1.785*	-5.585***	-4.091***	-4.273***
	(1.110)	(1.030)	(1.492)	(1.441)	(0.759)	(1.016)	(1.213)	(0.798)	(1.130)
DXY	2.721**	2.685**	0.519	5.046***	2.497***	0.792	4.560***	3.675***	3.039***
	(1.305)	(1.054)	(1.449)	(1.455)	(0.756)	(1.243)	(1.606)	(0.885)	(1.097)
DCredit X FCI	0.038	-0.021	0.019	-0.017	-0.025	0.004	0.006	-0.014	0.019
	(0.047)	(0.027)	(0.026)	(0.030)	(0.026)	(0.026)	(0.025)	(0.024)	(0.024)
Average Z-score	0.002	-0.001	-0.004**	0.004	0.002	-0.001	0.004**	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
RCO	-0.154	-0.118	0.039	-0.213**	-0.115	-0.104	-0.197**	-0.130	-0.106
	(0.109)	(0.086)	(0.103)	(0.092)	(0.082)	(0.082)	(0.099)	(0.083)	(0.085)
Observations	674	674	674	638	638	638	600	600	600

Table 5. RCO and Growth at Risk: Robustness Analysis (concluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
	Q=20	Q=50	Q=80	Q=20	Q=50	Q=80	Q=20	Q=50	Q=80
B. Robustness to method, sample, and riskiness measure									
(a) MSS	-0.206	-0.094	0.006	-0.238*	-0.142*	-0.073	-0.224**	-0.150**	-0.083
	(2.651)	(1.129)	(0.270)	(0.137)	(0.082)	(0.105)	(0.111)	(0.074)	(0.104)
(b) Restricted sample	-0.235*	-0.078	0.049	-0.295***	-0.182**	-0.087	-0.217**	-0.145	-0.184**
	(0.123)	(0.094)	(0.134)	(0.110)	(0.085)	(0.095)	(0.090)	(0.096)	(0.080)
(c) RCO Synthetic EDF	-0.322***	-0.145*	-0.090	-0.292***	-0.209***	-0.186**	-0.234***	-0.282***	-0.143
	(0.124)	(0.081)	(0.084)	(0.078)	(0.077)	(0.075)	(0.073)	(0.062)	(0.089)

The table reports quantile regressions of the one to three-year forward (h=1, 2, 3) relationship between Real GDP Growth (the dependent variable) and the (t=0) RCO, controlling for a series of macro variables. For each horizon h, the 3 columns reported show the coefficients of quantile regressions for the twentieth, fiftieth, and eightieth percentile using the Canay (2011) method for panel quantile regressions (with bootstrapped standard errors). Explanatory variables enter the regression as the lag of their simple three-year moving average. Real GDP growth is the annual rate of growth of real GDP, Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. FCI is the financial conditions index, built as described in the Appendix 3 and Global FCI is the world average of this index. RCO corresponds to the z-score based measure of the riskiness of credit origins. CA/GDP is the change in the ratio of current-account-to-GDP, DCreditXFCI

Is the interaction of the change in the credit-to-GDP ratio and the financial conditions index, VIX is the log of the CBOE VIX volatility index, and DXY is the log of the dollar index (DXY). Panel B reports the coefficients of the baseline regression. Each entry in Panel B corresponds to a different quantile regression. Only the coefficient for RCO is reported and the rest are omitted for space reasons. Regressions in row (a) use the Machado and Santos-Silva (2019) method for panel quantile regressions, while rows (b) and (c) use the baseline Canay method. Row (b) uses the restricted sample that requires that a country-year has at least 20 eligible banks to be included. In rows (a) and (b) RCO corresponds to the z-score based measure of the riskiness of credit origins, while row (c) uses the measure based on the synthetic EDF indicator. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 6. Asset Quality Channel: Bank Riskiness and Loan Portfolio Riskiness

	Flow of Loan Loss Provisions (basis points)				Change in Non-Performing Loans (basis points)				Leveraged Loans Share (percent)		
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)
	h=1	h=2	h=3		h=1	h=2	h=3		h=1	h=2	h=3
Riskiness	-0.705*	-1.322***	-1.333***		-4.694***	-5.280***	-4.895***		-0.725*	-0.560*	-0.494
	(0.393)	(0.391)	(0.456)		(0.813)	(0.730)	(0.671)		(0.379)	(0.298)	(0.364)
High Loan Growth	-3.064	-1.399	3.525		7.896	3.986	5.129		-8.576**	-4.734*	-1.798
	(2.297)	(2.189)	(2.281)		(5.081)	(4.245)	(3.785)		(3.508)	(2.581)	(3.048)
Riskiness X High Loan Growth	0.777*	1.421***	1.401***		3.389***	3.642***	3.412***		1.258**	0.945**	0.529
	(0.441)	(0.433)	(0.462)		(1.002)	(0.848)	(0.755)		(0.490)	(0.381)	(0.426)
Observations	27,204	23,907	20,919		21,266	18,768	16,751		1,675	1,562	1,481
R-squared	0.746	0.794	0.836		0.375	0.482	0.558		0.480	0.518	0.529
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The table reports the coefficients of bank-level local projection OLS regressions between a bank's flow of loan loss provisions (columns (1) to (3)), its change in nonperforming loans (columns (4) to (6)), and the share of leveraged and highly leveraged loans in total syndicated lending (Leveraged Loan Share, columns (7) to (9)), at 1 to 3-year ahead forecasting horizons High Loan Growth is a dummy that takes the value 1 when a bank's annual growth rate of a is above the median value in that country-year. Riskiness is the bank-level measure of riskiness, which in all these regressions corresponds to a bank´s z-score, which is the sum of a bank's return on average assets and leverage ratio, divided by the historical (three-year) standard deviation of its returns on average assets. The variable is expressed in deciles of the within country-year bank distribution. Regressions include country-year fixed effects, bank fixed effects, and bank controls that measure a bank´s share of total credit and its liquidity ratio. Standard errors are clustered at the bank level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 7. Asset Quality Channel: Controlling for the Riskiness of Credit Allocation in Growth-at-Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
	Q=20	Q=20	Q=20	Q=20	Q=20	Q=20	Q=20	Q=20	Q=20
Real GDP Growth	0.242***	0.252***	0.195**	0.152*	0.137	0.150**	0.103	0.110**	0.089
	(0.088)	(0.086)	(0.083)	(0.086)	(0.083)	(0.066)	(0.063)	(0.050)	(0.060)
Δ(Credit/GDP)	-0.100**	-0.106***	-0.085*	-0.116***	-0.118***	-0.111***	-0.117***	-0.115***	-0.112***
	(0.042)	(0.034)	(0.044)	(0.025)	(0.022)	(0.022)	(0.016)	(0.017)	(0.018)
FCI	0.627***	0.480**	0.618***	0.698***	0.668***	0.654***	0.397*	0.404**	0.485***
	(0.227)	(0.242)	(0.226)	(0.187)	(0.201)	(0.169)	(0.203)	(0.167)	(0.184)
Global FCI	-0.542*	-0.433	-0.507*	-1.059***	-0.934***	-1.024***	-0.955***	-0.973***	-1.023***
	(0.285)	(0.280)	(0.293)	(0.265)	(0.284)	(0.222)	(0.248)	(0.185)	(0.208)
RCA	-0.453*		-0.404	-0.678***		-0.470*	-0.237		-0.109
	(0.264)		(0.274)	(0.227)		(0.250)	(0.149)		(0.161)
RCO		-0.238**	-0.158		-0.381***	-0.309***		-0.274***	-0.261***
		(0.104)	(0.115)		(0.086)	(0.078)		(0.067)	(0.079)
Observations	636	636	636	603	603	603	568	568	568

The table reports results of quantile regressions of the one to three-year forward (h=1, 2, 3) relationship between the 20th percentile of Real GDP Growth (the dependent variable) and the RCO and RCA. The panel quantile regression methodology is Canay (2011) with bootstrapped standard errors. Explanatory variables enter the regression as their three-year moving average. Real GDP growth is the annual rate of growth of real GDP, Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. FCI is the financial conditions index, built as described in Appendix 3 and Global FCI is the world average of this index. RCA is based on Brandao et al. (2022). RCO corresponds to the z-score-based measure of the RCO. * p<10 percent, ** p<5 percent, *** p<1 percent

Table 8. Sentiment Channel: RCO and Future Changes in Bank Lending Standards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
RCO	0.142*		0.115**	0.143*		0.152*	0.061		0.078
	(0.072)		(0.052)	(0.073)		(0.075)	(0.069)		(0.071)
BLS		0.406***	0.399***		-0.084	-0.095		-0.183**	-0.189**
		(0.066)	(0.063)		(0.095)	(0.091)		(0.075)	(0.073)
Observations	379	379	379	349	349	349	320	320	320
R-squared	0.299	0.412	0.420	0.320	0.312	0.327	0.316	0.341	0.345
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

The dependent variable is the change in bank lending standards at h=1,2,3 years ahead horizons. A higher value means tighter lending standards. RCO corresponds to the z-score-based measure of the RCO and enters the regression as its lagged three-year moving average. BLS is change in bank lending standards in year t. All regressions include country and year fixed effects. Standard errors are clustered at the country level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 9. Sentiment Channel: RCO and Future Changes in Financial Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
RCO	-0.053**		-0.024	-0.050**		-0.024*	-0.021		0.000
	(0.025)		(0.015)	(0.021)		(0.012)	(0.016)		(0.018)
FCI		-0.294***	-0.287***		-0.234***	-0.225***		-0.159***	-0.159***
		(0.032)	(0.031)		(0.027)	(0.027)		(0.022)	(0.026)
Observations	689	689	689	651	651	651	611	611	611
R-squared	0.826	0.846	0.846	0.836	0.848	0.848	0.835	0.840	0.840
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

The dependent variable is the annual change in financial conditions at h=1,2,3 years ahead horizons. A higher value means looser financial conditions. RCO corresponds to the z-score-based measure of the RCO. Both RCO and FCI enter the regression as their lagged three-year moving average. All regressions include country and year fixed effects. Standard errors are clustered at the country level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 10. Sentiment Channel: Including Future Changes in FCI in Growth-at-Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
Real GDP Growth	0.367***	0.349***	0.359***	0.215***	0.166*	0.188**	0.238***	0.173**	0.238***
	(0.089)	(0.085)	(0.080)	(0.080)	(0.088)	(0.087)	(0.065)	(0.070)	(0.066)
Δ(Credit/GDP)	-0.088***	-0.116***	-0.076***	-0.122***	-0.121***	-0.120***	-0.140***	-0.128***	-0.121***
	(0.028)	(0.029)	(0.029)	(0.021)	(0.022)	(0.025)	(0.019)	(0.019)	(0.021)
FCI	0.606***	0.441*	0.619**	0.935***	0.768***	0.923***	0.643***	0.440**	0.573***
	(0.222)	(0.242)	(0.250)	(0.191)	(0.213)	(0.210)	(0.161)	(0.191)	(0.167)
Global FCI	-0.099	-0.352	-0.147	-0.675***	-1.052***	-0.716***	-0.737***	-0.960***	-0.759***
	(0.226)	(0.275)	(0.243)	(0.225)	(0.267)	(0.251)	(0.185)	(0.216)	(0.196)
ΔFCI (t+1)	0.289**		0.299***	0.799***		0.766***	0.540***		0.484***
	(0.117)		(0.110)	(0.110)		(0.110)	(0.109)		(0.098)
RCO		-0.186	-0.134		-0.311***	-0.130		-0.278***	-0.264***
		(0.113)	(0.094)		(0.089)	(0.101)		(0.071)	(0.078)
Observations	678	678	678	642	642	642	604	604	604

The table reports results of quantile regressions of the one to three-year forward (h=1, 2, 3) relationship between the 20th percentile of Real GDP Growth (the dependent variable) and the RCO and the change in financial conditions ΔFCI at time t+1, controlling for a series of macro variables. For each horizon h, the 3 columns reported show the coefficients of a quantile regression for a specification with ΔFCI only, RCO only, and both ΔFCI and RCO included respectively. The Canay (2011) method for panel quantile regressions (with bootstrapped standard errors) is used. Except for the change in financial conditions, explanatory variables enter the regression as the lag of their simple three-year moving average. Real GDP growth is the annual rate of growth of real GDP, Δ(Credit/GDP) is the change in bank credit between t and t-1 divided by contemporaneous GDP. FCI is the financial conditions index, built as described in the Appendix 3 and Global FCI is the world average of this index. RCO corresponds to the z-score based measure of the riskiness of credit origins. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 11. Resilience Channel: Bank Sector Stock Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1				h=2				h=3			
	τ=10	τ=20	τ=50	τ=80	τ=10	τ=20	τ=50	τ=80	τ=10	τ=20	τ=50	τ=80
A. Baseline												
RCO	-4.788**	-2.419	-0.454	0.503	-3.346**	-1.574	-1.420	-2.345	-2.798*	-1.573	-1.437	-3.398**
	(2.359)	(2.129)	(1.876)	(2.137)	(1.382)	(1.159)	(1.024)	(2.164)	(1.440)	(0.994)	(0.960)	(1.389)
Observations	630	630	630	630	630	630	630	630	596	596	596	596
B. Controlling for macro indicators												
RCO	-4.207*	-1.540	0.111	-0.337	-2.886*	-0.602	-0.867	-1.464	-1.999	-1.411	-1.215	-1.780
	(2.322)	(2.313)	(1.817)	(2.326)	(1.475)	(1.220)	(1.118)	(1.755)	(1.361)	(0.997)	(1.034)	(1.114)
Observations	626	626	626	626	626	626	626	626	592	592	592	592

The table reports results of panel quantile regressions of the one to three-year ahead (h=1, 2, 3) cumulative banking sector stock returns on the RCO. For each horizon h, the 3 columns reported show the coefficients of quantile regressions for the tenth, the twentieth, the fiftieth, and eightieth percentile using the Canay (2011) method for panel quantile regressions (with bootstrapped standard errors). RCO enters the regressions as its lagged three-year moving average. Panel A includes only real GDP growth, the change in credit to GDP, FCI, and global FCI (all as lagged three-year moving average) while Panel B includes an expanded set of macro controls (current account to GDP, log VIX, log DXY, the interaction of the change in credit to GDP and FCI, and average z-score). Standard errors are clustered at the bank level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 12. Resilience Channel: Bank Riskiness and Future Loan Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
High Loan Growth	2.461***	0.425**	-0.118	-0.630***	2.361***	0.365*	-0.228	-0.547**
	(0.174)	(0.167)	(0.186)	(0.188)	(0.201)	(0.199)	(0.216)	(0.231)
Riskiness	-0.224***	-0.107***	-0.069*	-0.010	-0.161***	-0.035	-0.025	0.034
	(0.035)	(0.037)	(0.039)	(0.038)	(0.040)	(0.043)	(0.046)	(0.047)
High Loan Growth X Crisis					0.459	-0.426	-0.477	-1.317***
					(0.432)	(0.458)	(0.471)	(0.484)
RiskinessX Crisis					-0.445***	-0.247**	-0.184**	-0.244**
					(0.084)	(0.096)	(0.092)	(0.097)
N	27224	24407	22079	20041	24391	21726	19366	17436
R-squared	0.504	0.511	0.512	0.524	0.515	0.521	0.521	0.535
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓

The dependent variable is a bank's average cumulative growth of gross loans at 1 to 4 years ahead horizons. High Loan Growth is a dummy that takes the value 1 when a bank's annual growth rate of a is above the median value in that country-year. Riskiness is the bank-level measure of riskiness, which in all these regressions corresponds to a bank´s z-score, which is the sum of a bank's return on average assets and leverage ratio, divided by the historical (three-year) standard deviation of its returns on average assets. Crisis is a dummy that takes the value 1 if a country is experiencing a systemic banking crisis according to Laeven and Valencia (2020). Standard errors are clustered at the bank level. * p<10 percent, ** p<5 percent, *** p<1 percent.

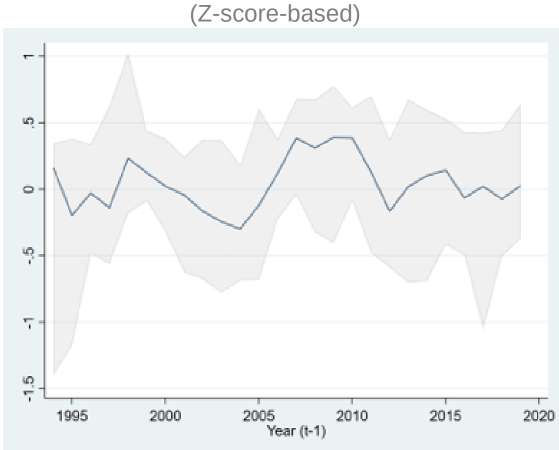
Table 13. Resilience Channel: Controlling for Banking Sector Fragility Indicators in Growth-at-Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
Leverage Skewness (t+1)	0.631		0.210	1.309		0.993	0.585		-0.290
	(0.804)		(0.765)	(0.906)		(1.008)	(1.265)		(1.167)
Average Riskiness (t+1)	-0.004***		-0.004***	-0.006***		-0.005***	-0.005***		-0.004***
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
RCO		-0.194*	-0.157		-0.302***	-0.304***		-0.299***	-0.224***
		(0.106)	(0.116)		(0.089)	(0.089)		(0.065)	(0.077)
Observations	667	667	667	632	632	632	595	595	595

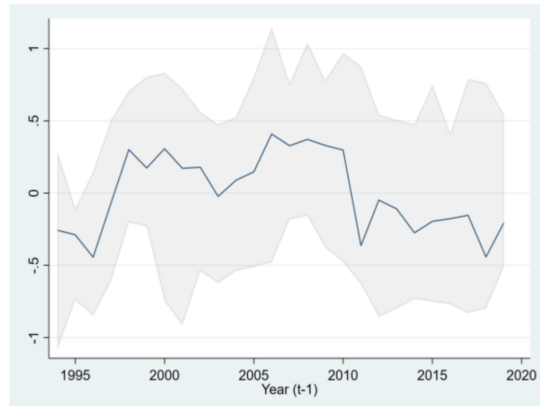
The table reports results of panel quantile regressions of the one to three-year forward (h=1, 2, 3) relationship between the twentieth percentile of Real GDP Growth (the dependent variable) and the RCO, average riskiness, and asset-weighted leverage skewness. For each horizon h, the 3 columns reported show the coefficients for a specification with both leverage skewness and average riskiness, a specification with RCO, and a specification with the three indicators included respectively. The Canay (2011) method for panel quantile regressions (with bootstrapped standard errors) is used. Control variables include Real GDP growth (the annual rate of growth of real GDP), change in bank credit to GDP ratio, financial conditions index (built as described in Appendix 3), and a global FCI (defined as the world average of this index). RCO corresponds to the z-score-based measure of the RCO. Leverage Skewness is the skewness of the asset weighted distribution of bank leverage (computed as total assets to total equity), within each country year. Average Riskiness is the simple average of the baseline measure of bank riskiness (negative z-score). Explanatory variables enter the regression as their three-year moving average, except for Leverage Skewness and Average Riskiness, which enter contemporaneously to the first year of the prediction horizon (t+1). * p<10 percent, ** p<5 percent, *** p<1 percent.

Figure 1. Evolution of the Global Distribution of the Two RCO Measures, and Evolution of the Z-score-based RCO measure in Selected Countries

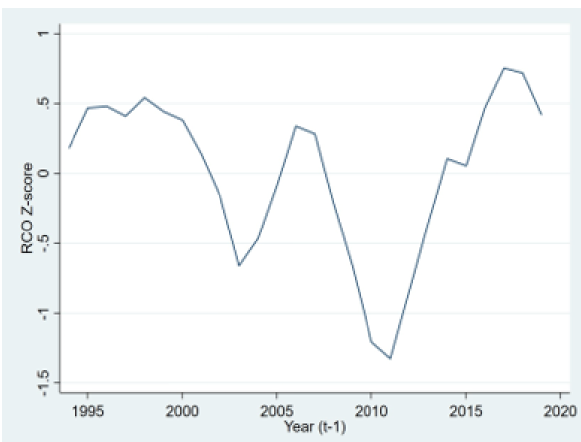
A. Evolution of the global distribution of RCO (Z-score-based)



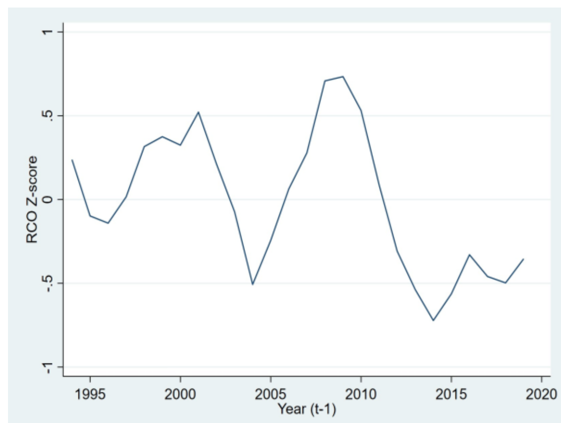
B. Evolution of the global distribution of RCO (Synthetic-EDF-based)



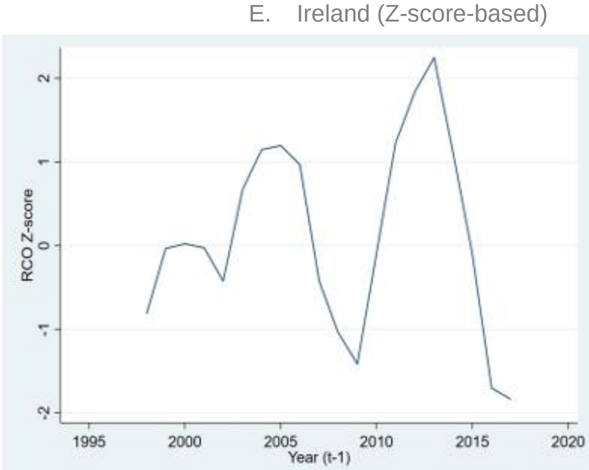
C. United States (Z-score-based)



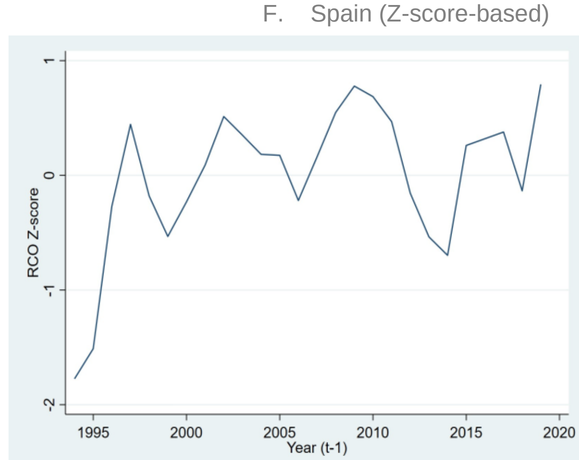
D. Germany (Z-score-based)



E. Ireland (Z-score-based)



F. Spain (Z-score-based)



Source: Authors' calculations

Appendix 1. List of Countries Included in the Sample

Country Name	Number of Banks	Country Name	Number of Banks
ARGENTINA	68	JAPAN	223
AUSTRALIA	46	KOREA (SOUTH), REPUBLIC OF	28
AUSTRIA	69	MALAYSIA	53
BELGIUM	44	MEXICO	47
BRAZIL	78	NETHERLANDS	48
BULGARIA	22	NEW ZEALAND	17
CANADA	59	NORWAY	51
CHILE	30	PERU	22
CHINA	112	PHILIPPINES	35
COLOMBIA	37	POLAND	46
CZECH REPUBLIC	28	PORTUGAL	51
DENMARK	33	RUSSIAN FEDERATION	103
FINLAND	12	SOUTH AFRICA	21
FRANCE	109	SPAIN	83
GERMANY	227	SWEDEN	29
GREECE	17	SWITZERLAND	238
HUNGARY	29	THAILAND	30
INDIA	65	TURKEY	30
INDONESIA	108	UNITED KINGDOM	90
IRELAND	28	UNITED STATES	400
ITALY	163	VIETNAM	42

Appendix 2. Synthetic EDF Estimation

As described in section III.A, we construct a measure of bank riskiness based on balance sheet indicators of bank fundamentals. Following the literature, we consider the following set of bank fundamentals related to the CAMEL/CAEL ratings approach originally developed by U.S. bank supervisors (see Purnandaram, 2007): capital adequacy (CAP), captured by the principal component of a bank's ratio of total equity to total assets and its z-score (as defined above), the ratio of loan loss provisions to total assets (LLP) capturing asset quality, the return on assets (ROA) as a measure of profitability, the cost-to-income ratio (CI) as a proxy for efficiency, and liquidity (LIQ), captured by the principal component of a bank's ratios of loans to assets, loans to deposits, liquid assets to total assets, and liquid assets to deposits. We construct this composite measure by running the following OLS regression:

$$EDF_{i,c,t}^{s} = \beta_1 CAP_{i,c,t}^{s} + \beta_2 LLP_{i,c,t}^{s} + \beta_3 ROA_{i,c,t}^{s} + \beta_4 CI_{i,c,t}^{s} + \beta_5 LIQ_{i,c,t}^{s} + \mu_{c,t} + \epsilon_{i,c,t}$$

Where EDF_{ict}^{s} is the (log) EDF of bank i, located in country c, in year t, and the superindex s denotes that the variables have been standardized to have a mean zero and standard deviation 1 across all observations. The sub- and superindexes in the explanatory variables refer to the same concepts. All variables were winsorized at a 1 percent level before being standardized. The parameter θ_{ct} represents a set of country-year fixed effects. Including these fixed effects implies that the estimation exploits how the different fundamentals relate to the EDF in the cross-section of banks within a country and year.[1]

Appendix Table 2.1 reports the estimated coefficients. It shows that higher capitalization and profitability reduce bank risk, while higher provisions, cost to income, or higher illiquidity increase risk.

We construct the synthetic risk index using the estimated coefficients for all banks with data on the relevant fundamentals, including those that do not have EDF data, as follows:

$$SRisk_{i,c,t}^{s} = \hat{\beta}_1 CAP_{i,c,t}^{s} + \hat{\beta}_2 LLP_{i,c,t}^{s} + \hat{\beta}_3 ROA_{i,c,t}^{s} + \hat{\beta}_4 CI_{i,c,t}^{s} + \hat{\beta}_5 LIQ_{i,c,t}^{s}$$

Notice that the construction does not include the estimated country-year fixed effects, so it does not capture a bank's level of riskiness but is an index of the differences in the riskiness of banks located in a given country in a given year. Including the country-year fixed effects would allow for the interpretation of the level of the index and its average variation in time within a country, at the cost of being able to construct it only for banks in a country-year when at least two banks had EDF data. Since our analysis will always controls for country-year fixed effects, this is not a problem. For the same reason, the synthetic risk indicator was normalized to have a mean of zero within a country.

[1] We used a LASSO OLS method with a selection criterion based on EBIC to allow the data select the relevant variables among the candidates. The method ended up selecting all variables, so the final specification is simply an OLS regression.

Appendix Table 2.1. Bank Synthetic Risk Index

Variable	Coefficient
CAP	-0.230***
	(0.0364)
LLP	0.139***
	(0.0301)
ROA	-0.0668*
	(0.0368)
CI	0.0847***
	(0.0303)
LIQ	0.157***
	(0.0419)
Observations	7595
R2	0.700
Adjusted R2	0.665

Appendix 3. Data Appendix

Data Sources and Definitions

Global-level, country-level, bank-level, and loan-level data sources, definitions, and transformations used in the paper are summarized in Appendix Table 3.1. Our credit series captures the credit to the private sector from domestic money banks and is preferred because it provides the greatest coverage. The change of the credit-to-GDP ratio is winsorized at the 1 percent level to reduce the influence of outliers. Banking sector merger and acquisitions data are sourced from Orbis M&A. Bank ownership data are sourced from Orbis and IMF (2015).

The financial conditions indices (FCIs) are estimated for 1990–2019 at a quarterly frequency for 42 advanced and emerging market economies using a set of eight price-based financial indicators (depending on availability of the individual series): (1) term spread; (2) corporate spread; (3) sovereign spread; (4) interbank spread; (5) first difference in real long-term rate; (6) equity returns; (7) equity volatility; and (8) house price returns. See Appendix Table 3.2 for data sources.

The FCIs are estimated using Koop and Korobilis' (2014) code available at: https://sites.google.com/site/dimitriskorobilis/matlab. This approach has two advantages. First, it can control for current macroeconomic conditions. Second, it allows for dynamic interactions between the FCIs and macroeconomic conditions, which can also evolve over time.

Bank-Level Dataset Construction

The full sample of bank financial statements available in the FitchConnect database was downloaded on two dates: June 11, 2018, and March 3, 2021. Each of these two files was subject to the following cleaning process:

Step 1 We select institutions in the FitchConnect universe based on their market sector description and their specialization.

We keep institutions with the following market sector description: bank holding companies, banks, credit union, development banks, private banks, retail & consumer banks, trade finance banks, trust & processing banks, universal commercial banks, wholesale commercial banks. We keep all institutions with the "commercial bank" specialization code. We also keep institutions with a market sector description of "government sponsored enterprises" when their specialization code is consumer loans / credit cards, co-operative banks, multi-lateral governmental banks, state / government bank, or savings bank. We drop all other institutions. We drop a handful of institutions that we know are not banks.

Step 2 We drop observations with missing data for total assets.

Step 3 We keep only annual statements.

Step 4 We keep only one statement quality type with the following order of priority: restated, original, preliminary, partial.

Step 5 We keep only one statement in cases where there are multiple audited/qualified categories available with the following order of priority: audited-unqualified, audited-qualified, and audited-unqualified (emphasis of matter) statements.

Step 6 We match BVD IDs identifiers (from Orbis) with Fitch IDs identifiers (from Fitch Connect)

Step 7 We keep only one statement in case multiple statements are available with different accounting standards, with the following order of priority: international financial reporting standards (IFRS), international accounting standards, local generally accepted accounting principles (GAAP), U.S. GAAP, regulatory.

Step 8 We match each bank with its global ultimate owner (GUO) in any given year. Historical ownership information from 2007 onward is sourced from FitchConnect/BvD historical ownership database. Historical ownership information for 1999-2006 is sourced from IMF (2015). Whenever ownership information is missing in the early years of the bank-level series but our ownership data indicate that the bank had a GUO during the first year for which we have ownership data, we assume that the bank was owned by this GUO during all previous years.

Step 9 We keep consolidated financial statements only when both consolidated and unconsolidated statements are available. If a consolidated statement is not available, we keep the unconsolidated statement.

Step 10 Based on the GUO information, we drop banks that are subsidiaries when their GUO is in the same country and is in the dataset. This is to avoid double counting at the country level. Additionally, we manually drop some banks that we know are part of a larger banking group domiciled in the same country when we have data on the consolidated entity (e.g., savings banks in Austria).

Step 11 We identify mergers using Orbis M&A data.

Step 12 We tag bank-years that have very high annual loan growth in absolute terms (>=200 percent) or relative to their recent history to capture M&A missing from the Orbis M&A data or other related structural changes. We also tag bank-years when Orbis M&A indicates a merger and loan growth is very high both relative to the bank's recent history and relative to other banks in the country in that year.

Step 13 We tag bank-years when there is an accounting system change.

Step 14 We merge our data with CreditEdge data (EDFs).

Starting from the cleaned 2021 vintage, we then add the bank-years that are in the 2018 vintage but are not in the 2021 vintage.

In our analysis, we exclude bank-years associated with a change in consolidation level (step 9), large merger (step 12), a change in accounting standards (step 13). We also exclude bank-years for which loan growth is missing.

We then restrict our sample to countries with a sufficiently large number of banks per year over a reasonably long period. The construction of our baseline sample starts by including only banks with total assets above 0.5 percent of the total assets of their country's largest bank during at least one year and with at least five years of data. Next, for each country, we keep only those years with at least ten banks meeting the criteria above, count the number of these years per country, and keep only those countries with at least five years meeting all these conditions in our sample. Finally, we keep only those countries where we could build a FCI because the macrofinancial literature on the credit cycle has emphasized the importance of considering price measures of the state of the cycle. This process yields a sample with 44,515 total bank-year observations, out of which 39,730 have the required information to construct the z-score (also considering the lags required to compute the standard deviation of ROA). These observations come from 3,071 banks in 42 countries from 1990 to 2019.

We also constructed an alternative (restricted) sample considering only country years with at least 20 banks and check the robustness of our results in this sample.

The dataset is identical for the construction of the country-level RCO measure and the bank-level analysis.

Loan-level Dataset Construction

Using Dealogic's global transaction-level syndicated loan database, we construct annual bank-level Leveraged Loan Share (LLS) of new loans. LLS measures the share of leveraged and highly leveraged syndicated loans in a bank's new syndicated loan portfolio for a given year. The database includes information on individual borrowers, participating lenders, and loan allocation amounts for each lender in a syndication. We first exclude observations with missing allocation amounts or without a loan generation date. We then manually match the Dealogic data with our bank-level dataset using fuzzy matching techniques on the names of lenders and their parent bank. This results in a final dataset that aligns the deal information with the financial statement data of each participating lender (around 700,000 tranche-lender-level observations). We retain only banks that participate in at least 20 syndicated loan tranches in a given year to ensure sufficient loan transaction observations for constructing LLS. The regression sample consists of 1676 bank-year observations from 1993 to 2019, covering 99 banks from 17 countries. The average LLS in the regression sample is 22.6 percent.

Appendix Table 3.1. Data Sources and Definitions

Variable	Description	Source
Global variables		
VIX	Logarithm of the Chicago Board Options Exchange Volatility Index.	Bloomberg Finance L.P.
US Dollar Index (DXY)	Weighted geometric mean of the U.S. dollar's exchange rate against a basket of currencies (euro, Japanese yen, Pound sterling, Canadian dollar, Swedish krona, and Swiss franc)	Bloomberg Finance L.P.
Country-level variables		
Real GDP growth	Annual percentage change in the gross domestic product, constant prices in national currency.	IMF, WEO database
Nominal GDP	Gross domestic product, current prices in national currency.	IMF, WEO database
Bank credit	Total credit from banks to the private sector	IMF, IFS database
Current account	Current account balance, in US dollars.	IMF, WEO database
Exchange rate	National currency per US dollar.	IMF, IFS and WEO
Financial Conditions Index	For methodology and variables included in the FCI, see Appendix 3 and Appendix Table 3.2. Positive values of the FCI indicate looser-than-average financial conditions.	Authors' estimates
Riskiness of credit allocation	Difference between average riskiness decile of top corporate debt issuers and average riskiness decile of bottom corporate debt issuers, with riskiness measured by the debt-to-assets ratio	Authors' calculations based on Brandao-Marques et al. (2022) and Worldscope
Change in Lending Standards	The difference between the fraction of banks responding to loan officer opinion surveys that declare having tightened their lending standards relative to the previous quarter and the fraction that declare having loosened their lending standards. When a survey covers different types of lending, the commercial and industrial loan segment is used. In countries that do not have such a survey but have lending condition indexes, the latter are used. All series are standardized within country.	Haver Analytics
Systemic Banking Crisis	Dummy variable indicating whether a country is in a systemic banking crisis	Laeven and Valencia (2020)
Banking Sector Stock Returns	Annual percentage change in the Datastream banking sector stock index.	LSEG Datastream

Appendix Table 3.1. Data Sources and Definitions (concluded)

Variable	Description	Source
Bank-level Variables		
Z-score	Sum of return on average assets and leverage ratio, divided by the historical (3-year) standard deviation of return on average assets	Authors' calculations based on Fitch Connect
Return on Average Assets	Net income divided by average assets	Fitch Connect
Leverage Ratio	Total equity divided by total assets	Fitch Connect
Loan Loss Provisioning	Flow of loan loss provisions	Fitch Connect
Loan Loss Provisions	Stock of loan loss provisions	Fitch Connect
Cost to Income Ratio	Total operating expenses divided by operating income (sum of net interest income and other income)	Fitch Connect
Loans to Assets Ratio	Total loans divided by total assets	Fitch Connect
Loans to Deposit Ratio	Total loans divided by total deposits	Fitch Connect
Liquid Assets Ratio	Liquid assets divided by total assets	Fitch Connect
Liquid assets to deposits	Liquid assets divided by total deposits	Fitch Connect
Expected Default Frequency	Expected default frequency at a 1-year horizon, annual average	Moody's CreditEdge
Non-performing Loans Ratio	Non-performing loans divided by total loans	Fitch Connect
Total Loans	Total loans	Fitch Connect
Total Debt	Total assets minus total equity	Fitch Connect
Total Assets	Total assets	Fitch Connect
Total Equity	Total equity	Fitch Connect
Bank Loan Market Share	Ratio of gross loans to total bank credit	Fitch Connect, IFS
Share of leveraged loans issuance	For construction methodology, see Appendix 1	Authors' calculations based on Dealogic data

Appendix Table 3.2. Data Sources for the Input Series of the Financial Conditions Index

Variable	Description	Source
Term Spread	Yield on 10-year government bond minus yield on 3-month Treasury bill	Bloomberg Finance L.P.
Interbank Spread	Interbank interest rate minus yield on 3-month Treasury bill	Bloomberg Finance L.P.
Change in Long-Term Real Interest Rate	Percentage point change in the 10-year government bond yield, adjusted for inflation	Bloomberg Finance L.P.
Corporate Spread	Corporate yield of the country minus sovereign yield of the benchmark country; JPMorgan Corporate Emerging Markets Bond Index Broad is used for emerging market economies where available.	Bloomberg Finance L.P.; Thomson Reuters Datastream
Equity Returns (local currency)	Log difference in equity index	Bloomberg Finance L.P.
House Price Returns	Log difference of the house price index	BIS, Haver Analytics
Equity Return Volatility	Exponential weighted moving average of equity returns	Bloomberg Finance L.P.
Sovereign Spread	Yield on 10-year government bond minus the benchmark country's yield on 10-year government bond	Bloomberg Finance L.P.

PUBLICATIONS

The Riskiness of Credit Origins and Downside Risks to Economic Activity
Working Paper No. WP/2024/XX