The Riskiness of Credit Origins and Downside Risks to Economic Activity

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Abstract

We construct a measure of the extent to which country-level 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 three decades, we document that RCO varies with the credit cycle. RCO also robustly predicts downside risks to GDP growth even after controlling for standard determinants like aggregate credit growth and financial conditions. RCO's explanatory power comes from its relationship with credit quality, investor sentiment, and future banking sector resilience. Our findings underscore the importance of bank heterogeneity for credit cycle theories.

Keywords: Private sector debt; credit growth; credit origin; credit cycle; bank soundness; credit risk; financial vulnerability; investor sentiment; financial stability

JEL Codes: E44, E47, G01, G21, G28

1 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 (Jordà et al., 2011; Schularick and Taylor, 2012; Mian et al., 2017, 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; Kirti, 2021; 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 following 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). At the epicenter of the Spanish banking crisis a decade ago, Spanish savings banks experienced a continuous rise in their loan market share ahead of the crisis (Santos, 2017). 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 Vihriälä, 2016).

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 Sannikov, 2014).[1] 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, 2024; Jamilov and Monacelli, 2024).

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.[2] Furthermore, we provide country- and bank-level analyses to explore the underlying mechanisms of our key results.

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 capturing the composition of aggregate debt issuance across heterogeneous borrowers. We present evidence that our measure, the Riskiness of Credit Origins (RCO), rises when aggregate credit growth increases and financial conditions loosen. 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

[1]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 a single agent represents each sector 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.

[2]In the paper, we use the expressions "riskier bank" and "weaker bank" interchangeably.

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 points 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 greater loan loss provisions and nonperforming loan ratios later. This increase is even stronger when the bank is ex-ante riskier (with a lower relative z-score). We also use syndicated loan origination data to show that riskier banks lend relatively more to ex-ante riskier borrowers when expanding their loan portfolios. At the macro level, we also analyze whether RCO's explanatory power for downside risks to growth is affected by including a variable capturing a riskier allocation of credit (Brandão-Marques et al., 2022) in the specification. We find that it does at horizons of 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 changes in aggregate bank lending standards and financial conditions. We find it does at horizons of up to two years for bank lending standards and financial conditions. Both findings strongly support a sentiment channel.[3]

[3]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.

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 relatively riskier banks contribute to expanding 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 extreme left tail of banking sector stock returns, consistent with a resilience channel.[4]

The rest of the paper is structured as follows. Section 2 discusses the theoretical underpinnings of the relationship between bank riskiness, risk-taking, and credit cycle and reviews the relevant theoretical and empirical literature. Section 3 introduces our measure of the RCO. Section 4 analyzes its co-movement with aggregate changes in bank credit and provides related bank-level evidence. Section 5 documents RCO's predictive power for future downside risks to growth while Section 6 presents our analysis of the three possible channels underlying this relationship. Section 7 concludes. Appendices provide additional information on data sources, variables construction, sample construction, and additional robustness analyses.

[4]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.

2 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.[5] Low bank capitalization also reduces the incentives to monitor loan quality because of market imperfections (Holmstrom and Tirole, 1997; Allen et al., 2011).[6] 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 Bhattacharya, 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 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 be-

[5] 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.

[6] Conversely, under limited liability, banks with higher risk appetite choose to be more leveraged and riskier Coimbra and Rey (2024).

cause of the debt overhang problem (Myers, 1977) , the relaxation of standards in good times is likely stronger among them. In Coimbra and Rey (2024), 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 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 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 Pinheiro (2011) and Igan and Tamirisa (2016) find that weaker banks grow their loan portfolios more slowly than stronger banks in normal times but at the same pace 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 (Jiménez et al., 2014; Dell'Ariccia et al., 2017). We complement this literature by focusing on a broader sample of countries and the credit cycle rather than on changes in monetary policy in a single jurisdiction.

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, 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 credit quality channel builds on several empirical papers that have examined the bank-level relationship between the 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, 2016), 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, showing that bank-level riskiness amplifies the effect of loan portfolio growth on future performance. In addition, in a smaller sample of banks, we document that ex-ante credit quality (measured by the share of leveraged loan issuance in total loan issuance) is greater in riskier and faster-growing banks. Our discussion of the credit quality channel at the country level relates to the macro literature on lending standards and GDP growth (Greenwood and Hanson, 2013; Kirti, 2021; Brandão-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; Petersen and Rajan, 1994; Hubbard et al., 2002; Elyasiani and Goldberg, 2004;

López-Espinosa et al., 2017; 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 (2018) do not relate their indicator to financial stability outcome variables.

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. Goldstein et al. (2023) also study the aggregate consequences of the composition of the banking sector, emphasizing a mechanism where banks' heterogeneity in their exposure to runs enhances aggregate stability. Our work relates to this analysis by showing that a dimension of banking sector similarity, the extent to which a credit expansion is driven by banks with a more pronounced risk profile, worsens future financial stability outcomes.

3 Riskiness of Credit Origins Measurement and Samples Construction

3.1 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 riskiness and assign each bank its decile position in the distribution (a higher decile corresponds 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.[7] Finally, we take the difference between these two averages. Formally, the measure is defined as follows:

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

where $Risk(decile)_{i,c,t}$ is the decile in the distribution of bank i's riskiness measure in country c at time t. $N_{c,t}^{Top}$ 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 the riskiness of credit origins within countries and not on its absolute level, 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 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.[8] 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

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

[8] See Laeven and 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.

(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 Purnanandam, 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 credit 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.[9] 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) using 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 projecting, 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 A for a detailed explanation).

[9]Beltratti and Stulz (2012) analyze the role of capital, profitability, liquidity, and governance quality in explaining bank stock market performance in the early stages of the GFC

3.2 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, 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 International Monetary Fund (2015)) and mergers and acquisitions data (sourced from Orbis M&A).[11] The ownership data is used to drop 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 B 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

[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.

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

yields a sample with 44,515 total bank-year observations, 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 Table B.1). We also construct a restricted sample considering only country-years with at least 20 banks satisfying the above criteria and check the robustness of our results in this sample.

Macrofinancial data sources, definitions, and transformations used in the paper are summarized in Appendix B, Table B.2. 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 each country's annual average of quarterly FCIs to measure 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 Brandão-Marques et al. (2022) using Worldscope data.

Table 1 reports summary statistics for our baseline sample, separating 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.[13] 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

[13]This is largely due to the use of a three-year rolling standard deviation of ROA in the calculation of our benchmark measure. Using the full history of ROA (i.e. considering past and future values) renders values closer to 50, which is standard in the literature

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 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 ΔNPL) 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 equal to 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.

4 The Cyclicality of the Riskiness of Credit Origins

Before diving 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 riskiness measure (z-score). 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 GFC, 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 banking crisis.

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

$$RCO_{c,t+h} = \alpha_{1,h}\Delta(\frac{Credit}{GDP})_{c,t} + \alpha_{2,h}FCI_{c,t} + \alpha_{3,h}Growth_{c,t} + \mu_{c,h} + \xi_{t,h} + \epsilon_{c,t+h} \qquad (2)$$

where $RCO_{c,t+h}$ is the riskiness of credit origin in country c in year $t+h$ $(h = 0,1)$; $\Delta(Credit/GDP)_{c,t}$ 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) $Growth_{c,t}$ is the annual real GDP growth rate and $\mu_{c,h}$, and $\xi_{t,h}$ 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 credit expansion leads to 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, a statistically significant relationship exists 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 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:

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

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.[14] To be consistent with our definition of RCO, the variable $Riskiness_{i,c,t-1}$ 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 that includes the liquid asset ratio and bank loan market share (to capture size in the loan market). θ_i and $\mu_{c,t}$ correspond to bank and country-year fixed effects respectively. Standard errors are clustered at the bank level. All bank-level variables except for $Riskiness_{i,c,t-1}$ 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 riskiness 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 eighth decile of the z-score distribution.

The pattern is similar for the expansion in total assets or total debt. The growth of assets

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

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)). These findings indicate that bank riskiness heterogeneity tends to drive the bank credit cycle.

For the country-level regressions, we also check whether our results are robust to the choice of sample or bank riskiness measure. Panel B of Table 2 presents the key coefficient for the interaction of bank riskiness and size of credit expansion for various specifications that use our alternative samples and 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 adverse macrofinancial outcomes often follow large credit expansions. Not only do such expansions increase leverage in the financial and non-financial 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.

5 Riskiness of Credit Origins and Downside Risks to Growth

Having established that the distribution of the origins 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 credit expansion 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 of the one- to three-year-ahead average cumulative GDP growth distributions:

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

where $\Delta y_{c,t,h}$ is the 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 (the average 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 (Jordà et al., 2011, following), 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.[15] The function $Q\left(\tau, x\right)$ denotes percentile τ of variable x. Following the literature (Mian et al., 2017; Brandão-Marques et al., 2022, among others), all explanatory variables enter the equation as their three-year moving average (*mv3* superscript).[16]

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.[17] In (4), the dependence on τ of the coefficients captures that they can vary across these percentiles. We 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 us-

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

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

[17]Our choice of percentiles on each side of the distribution reflects a compromise between our interest in analyzing extreme events and our decreasing confidence in the precision of the estimates as we get deeper into the tails given our small sample size (about 600 observations).

ing Canay (2011)'s method which assumes that the country fixed-effects are common across percentiles (i.e. $\mu_{c,h}(\tau) = \mu_{c,h}$ for each τ), but check the robustness of our findings 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. The methods available for estimating this class of non-linear models do not allow for the inclusion of time fixed-effects, making 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 5, columns 1-3). In other words, RCO has a significant predictive power for future downside risks to growth.[18] 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 $h = 2$ year horizons. A one-standard-deviation increase in RCO moves the left tail of the two-year ahead average annual real GDP growth distribution by 31 basis points, which is sizeable. In line with the existing literature, stronger credit growth worsens future downside risks to GDP growth (regardless of the distribution percentile). Looser global financial conditions also lead to a 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 two and three-year horizons, the coefficient for RCO

[18] We also ran a specification that 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.

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 (2019) (row (a)), our restricted sample (row (b)), and RCO based on the synthetic EDF measure of riskiness (row (c)).[19] 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 two and three-year horizons.

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

6 Why Does RCO Predict Downside Risks? Exploring the Channels

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

[19]The full set of coefficients for the regressions reported in this panel is in Appendix Table C.1

portfolio (credit quality channel). Second, a high RCO could capture a buoyant sentiment in the banking sector or financial markets (sentiment channel). Third, changes in RCO could capture variations in the concentration of an economy's loan portfolio in riskier banks, which are 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.

6.1 Credit 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 a bank's portfolio riskiness. 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:

$$\begin{aligned} LLP_{i,c,t,h} &= \beta_h LLP_{i,c,t-1} + \gamma_{1,h} HLG_{i,c,t} + \gamma_{2,h} Riskiness_{i,c,t-1} \\ &\quad + \gamma_{3,h} Riskiness_{i,c,t-1} \times HLG_{i,c,t} + \gamma_{4,h}^{'} X_{i,c,t-1} + \theta_{i,c,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h} \quad (5) \\ DNPL_{i,c,t,h} &= \beta_h DNPL_{i,c,t-1} + \gamma_{1,h} HLG_{i,c,t} + \gamma_{2,h} Riskiness_{i,c,t-1} \\ &\quad + \gamma_{3,h} Riskiness_{i,c,t-1} \times HLG_{i,c,t} + \gamma_{4,h}^{'} X_{i,c,t-1} + \theta_{i,c,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h} \quad (6) \end{aligned}$$

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. $LLP_{i,c,t-1}$ and $DNPL_{i,c,t-1}$ are the lagged values of the flow of loan-loss provisions and the change in the stock of nonperforming loans of bank i in country c. $Riskiness_{i,c,t-1}$ 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, 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 performance measure, the interaction term coefficients are significant for all three time-horizons.[20]

To study whether the relationship between bank riskiness and borrower riskiness documented above extends to ex-ante measures of riskiness, we exploit syndicated loan data. Information on data sources and dataset construction for this specific analysis is provided in Appendix B. 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 an ex-ante perspective, it can be computed only for a small sample of banks (those that participate in the syndicated loans market).[21] We analyze its relationship to

[20] 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.

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

bank riskiness and loan portfolio growth using the following local projections regression:

$$LLS_{i,c,t,h} = \gamma_{1,h} HLG_{i,c,t} + \gamma_{2,h} Riskiness_{i,c,t-1} + \gamma_{3,h} Riskiness_{i,c,t-1} \times HLG_{i,c,t} \\ + \gamma^{'}_{4,h} X_{i,c,t-1} + \theta_{i,c,h} + \mu_{c,t,h} + \varepsilon_{i,c,t,h}, \quad (7)$$

where variable names and notation are the same as in Equation 5 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 risk-taking measures.

Having established the plausibility of the channel at the micro level, we turn 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. We use the leveraged-based RCA measure from Brandão-Marques et al. (2022). It is constructed using a logic similar to RCO and captures the extent to which more leveraged borrowers are expanding their debt relatively faster. We include RCA in the regression, similarly to RCO, as a three-year moving average. Table 7 presents the 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 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 the one-year horizon, and decreases its size at longer horizons without affecting its significance.[22] Thus, while the micro evidence indicates the validity of the credit quality channel, an aggregate proxy for credit 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 at

[22]The analysis also indicates that RCO's predictive power is more persistent that RCA's.

least as good an aggregate proxy for credit quality or that other channels are at play.

6.2 Sentiment Channel

We next explore the possibility that RCO could capture banking sector sentiment or investor sentiment. In the spirit of López-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 officer surveys. The surveys measure the difference between the fraction of officers who declared having tightened their lending standards and those who declared having loosened them.[23] These data are available for a subsample of 31 countries and for a shorter timespan than RCO (we have more than five countries with data available only after 2003). This reduces the sample size by about half, so the results below must be interpreted with caution.

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

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

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 $\xi_{t,h}$ coefficients are country and year fixed effects, respectively. The results are presented in Panel A of 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

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

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 capture banking sector sentiment.

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

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

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 Panel B of Table 8 for three-time horizons (h=1,2,3). Again, for each time horizon, the first column shows the results of a specification with RCO only, the second column shows the results of a specification with FCI only, and the third column provides the results of a specification with both RCO and FCI included. A higher RCO helps predict future tightening in financial conditions 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. Further confirmation of this channel is provided by 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 9, including this term reduces the magnitude of the RCO coefficient and eliminates its significance at horizons of up to two years.[24]

6.3 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

[24] We also checked the robustness of our analysis of the sentiment channel by augmenting equations 8 and 9 with RCA on the right-hand side. This addition does not alter the results presented in Table 8.

the relationship between RCO and future banking sector stock returns. Arguably, if RCO predicts future downside risks to growth because it 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:

$$\begin{aligned} Q\left(\tau, r_{c,t,h}\right) = \alpha_{1,h}(\tau)\Delta\left(\frac{Credit}{GDP}\right)^{mv3}_{c,t} + \alpha_{2,h}\left(\tau\right)FCI^{mv3}_{c,t} + \alpha_{3,h}(\tau)RCO^{mv3}_{c,t} \\ + \alpha_{4,h}(\tau)' X^{mv3}_{c,t} + \mu_{c,h}(\tau) + \varepsilon_{c,t,h}(\tau) \end{aligned} \tag{10}$$

where $r_{c,t,h}$ is the h-year-ahead (h=1,2,3) banking sector index's 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) and include the tenth percentile to capture the very left tail of the distribution. Panel A of Table 10 reports the RCO coefficients of the baseline specification that includes only real GDP growth and global financial conditions in the set of controls ($X^{mv3}_{c,t}$) and the fixed effects as explanatory variables. Panel B of the same table reports results including the full set of macro controls described in Panel A of Table 5.[25] These results show that while RCO generally predicts adverse banking sector stock return performance, it mostly does so 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 left tail of the one-year-ahead banking sector 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 on average across time and following large adverse financial shocks. To this end, we estimate the parameters of the following bank-level local projections

[25] The full set of coefficients is reported in Appendix Table C.2

regression:

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

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 $t+h$. The rest of the notation is the same as in Equation 3. 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 11 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 only about half as large.[26] 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 5), and the skewness of the asset-weighted leverage distribution (constructed as in Coimbra and Rey (2018)). For

[26]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.

each of the three-time horizons (h=1,2,3), we examine 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 12). 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.[27] Turning to the RCO regression coefficient, we find that its magnitude declines by about 20 percent at the one-year and three-year horizons when controlling for the other two resilience fragility indicators, suggesting the presence of a resilience channel in the aggregate.[28]

Overall, the results suggest that part of RCO's explanatory power 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, accounting for this channel does not exhaust RCO's information about future downside risks to activity.

7 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 credit composition across heterogeneous banks. We construct a new measure of the riskiness of credit origins, which we label RCO, capturing the extent to which relatively riskier banks drive aggregate credit growth. 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 the size of credit expansion and financial conditions.

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

[28]We also checked the robustness of our resilience channel analysis by including RCA on the right-hand side of this specification. Results presented in Table 12 remain almost identical.

We also present evidence of three interrelated 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 credit 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 large adverse financial shocks, the banking sector's aggregate lending capacity is less resilient following periods when these banks have expanded relatively more.

Our paper complements recent work by Brandão-Marques et al. (2022) which documented the importance of accounting for the riskiness of credit allocation across borrowers in predicting financial crises and downside risks to growth. Our findings highlight the importance of also accounting for lender heterogeneity in empirical and theoretical models of the credit cycle, echoing recent work by Coimbra and Rey (2024) and Jamilov and Monacelli (2024). 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 considering lender heterogeneity in the calibration of macroprudential capital buffers. Future research based on a 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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Tables and Figures

Table 1: Summary Statistics

A. Bank-Level Variables

	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
Observations	39,730	41,085	43,091	44,515	32,004	30,298

B. Country-Level Variables

	RCO (z-score) (deciles)	RCO (synth. 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
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 non-performing loans to its lagged gross loans and DNPL is the change in nonperforming loans 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. FCI is the financial conditions index described in Appendix B. GDP growth is the annual growth rate of real GDP, and CA/GDP is the current account ratio 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	N	N	N	N	N	N	N	N
Year FE	N	N	Y	Y	N	N	Y	Y
	C. Alternative RCO measure				**D. Adding macro controls**			
	(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	0.006	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	N	N	N	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	N	N	Y	Y

The table reports the results of OLS regressions analyzing the contemporaneous (h=0) or one period forward (h=1) relationship between RCO and Real GDP Growth, the change in the credit-to-GDP ratio, and the financial conditions index (FCI). In panels A, B, 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 a country-year with 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 growth rate 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, as described in Appendix B. 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) Loan Growth	(2) Asset Growth	(3) Debt Growth	(4) 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	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y
B. Alternative Bank Riskiness Measure and Sample				
RCO (Synthetic EDF)	0.039***	0.028***	0.032***	0.005
	(0.010)	(0.009)	(0.009)	(0.012)
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 analyzing the relationship between the dependent variables shown at the top of each column and the explanatory variables listed in the first column. Loan Growth, Asset Growth, Debt Growth, and Equity Growth are the annual growth rates 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 the negative of 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. The lagged dependent variable corresponds to the one-year lagged value of the dependent variable, included to control for autocorrelation effects. Panel B reports results for the alternative measure of bank riskiness and the restricted sample. Only the Riskiness X Δ(Credit/GDP) interaction coefficient is reported for space reasons. In Row (a), Riskiness is the synthetic EDF indicator, and Row (b) uses the baseline (minus) 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 the results of quantile regressions analyzing the one- to three-year forward (h=1, 2, 3) relationship between Real GDP Growth (the dependent variable) and RCO, controlling for key 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 growth rate 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 B, 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	
	τ=20	τ=50	τ=80	τ=20	τ=50	τ=80	τ=20	τ=50	τ=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)

Continued on next page

Table 5 – continued from previous page

	(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
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
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 results of quantile regressions analyzing the one- to three-year forward (h=1, 2, 3) relationship between Real GDP Growth (the dependent variable) and RCO, controlling for key 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 growth rate 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 B, 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, DCredit X FCI 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 specification. Each entry in Panel B corresponds to a different quantile regression. Only the coefficient for RCO is reported and the other coefficients 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 (2011) method. Row (b) uses the restricted sample constructed by requiring 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: Credit Quality Channel: Bank Riskiness and Loan Portfolio Riskiness

	Flow of Loan Loss Provisions (basis points)			Change in Non-Performing Loans (basis points)			Leveraged Loan 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***	1.258**	0.945**	0.529
	(0.393)	(0.391)	(0.456)	(0.813)	(0.730)	(0.671)	(0.490)	(0.381)	(0.426)
High Loan Growth	-3.064	-1.399	3.525	7.896	3.986	5.129	-0.725*	-0.560*	-0.494
	(2.297)	(2.189)	(2.281)	(5.081)	(4.245)	(3.785)	(0.379)	(0.298)	(0.364)
Riskiness X High	0.777*	1.421***	1.401***	3.389***	3.642***	3.412***	-8.576**	-4.734*	-1.798
Loan Growth	(0.441)	(0.433)	(0.462)	(1.002)	(0.848)	(0.755)	(3.508)	(2.581)	(3.048)
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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y

The table reports the coefficients of bank-level local projections regressions of a bank's flow of loan loss provisions (columns (1) to (3)), its change in nonperforming loans (columns (4) to (6)), and its share of leveraged and highly leveraged loans in total syndicated lending (Leveraged Loan Share, columns (7) to (9)) on a set of determinants, at 1 to three-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 the negative of 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 its distribution across banks in a given country and year. 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: Credit 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	
	τ=20	τ=20	τ=20	τ=20	τ=20	τ=20	τ=20	τ=20	τ=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 analyzing the one- to three-year forward (h=1, 2, 3) relationship between the 20th percentile of Real GDP Growth (the dependent variable), 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 growth rate 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 B and Global FCI is the world average of this index. RCA is based on Brandão-Marques et al. (2022). RCO corresponds to the z-score-based measure of the riskiness of credit allocation. * $p<10$ percent, ** $p<5$ percent, *** $p<1$ percent

Table 8: Sentiment Channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
A. RCO and Future Changes in Bank Lending Standards									
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
B. RCO and Future Changes in Financial Conditions									
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

This table reports results of country-level local projections regressions analyzing the one- to three-year forward relationship between changes in bank lending standards and RCO. In Panel A, the dependent variable is the change in bank lending standards at h=1,2,3-year-ahead horizons. A higher value means tighter lending standards. BLS is the change in bank lending standards in year t. In Panel B, the dependent variable is the annual change in financial conditions at h=1,2,3-year-ahead horizons. A higher value means looser financial conditions. RCO corresponds to the z-score-based measure of the riskiness of credit origins and enters the regression as its lagged three-year moving average in both panels. In Panel B, FCI enters 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 9: 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 analyzing the one to three-year forward (h=1, 2, 3) relationship between the 20$^{\text{th}}$ percentile of Real GDP Growth (the dependent variable), 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 estimations use the Canay (2011) method for panel quantile regressions (with bootstrapped standard errors). 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 growth rate 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 B, 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 10: 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 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 averages). 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 country level. * p<10 percent, ** p<5 percent, *** p<1 percent.

Table 11: 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)
Riskiness X 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	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y

This table reports results of local projections regressions of future loan growth on bank riskiness. The dependent variable is a bank's average cumulative growth of gross loans at one to four-year-ahead horizons (h=1 to 4). 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 the negative of 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.

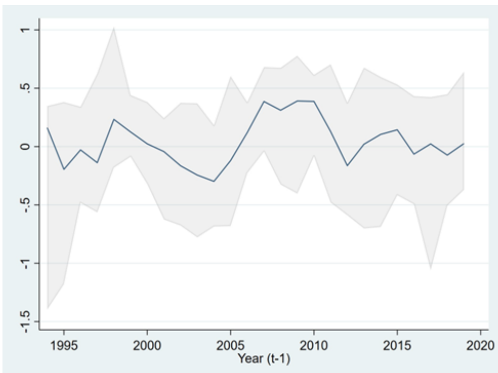
Table 12: Resilience Channel: Controlling for Banking Sector Fragility Indicators in Growth-at-Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=2			h=3	
Leverage Skewness	0.631		0.210	1.309		0.993	0.585		-0.290
(t+1)	(0.804)		(0.765)	(0.906)		(1.008)	(1.265)		(1.167)
Average Riskiness	-0.004***		-0.004***	-0.006***		-0.005***	-0.005***		-0.004***
(t+1)	(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

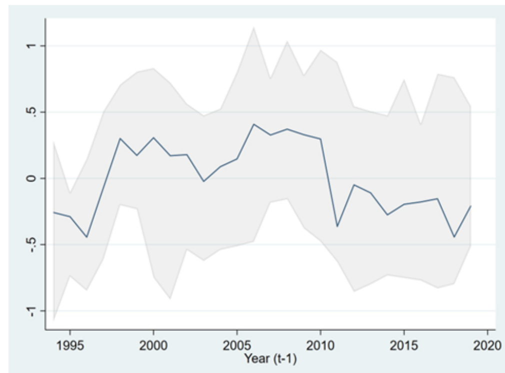
The table reports results of panel quantile regressions analyzing the one- to three-year forward (h=1, 2, 3) relationship between the twentieth percentile of Real GDP Growth (the dependent variable), RCO, average bank riskiness, and asset-weighted bank leverage skewness. For each horizon h, the 3 columns reported show the coefficients for a specification with leverage skewness and average riskiness, a specification with RCO, and a specification with the three indicators included respectively. The estimations use the Canay (2011) method for panel quantile regressions (with bootstrapped standard errors). 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 B), 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 of z-score). Explanatory variables enter the regression as their three-year moving average, except for Leverage Skewness and Average Riskiness, which enter contemporaneously with 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

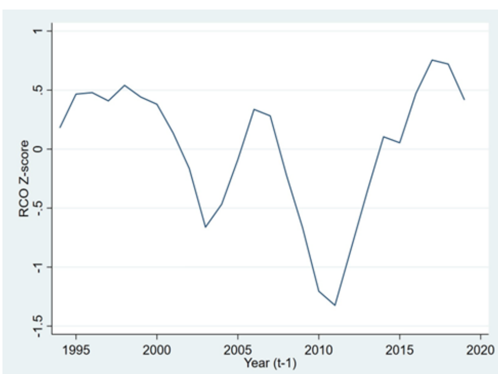
(a) Evolution of the global distribution of RCO (Z-score-based)



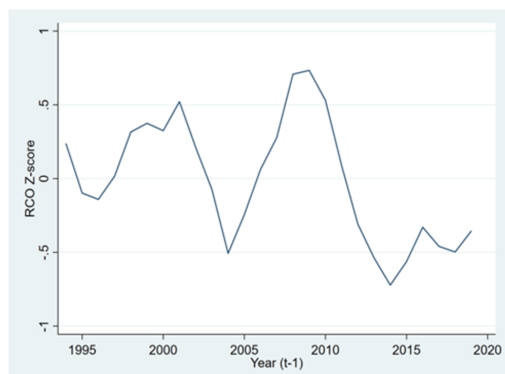
(b) Evolution of the global distribution of RCO (Synthetic-EDF-based)



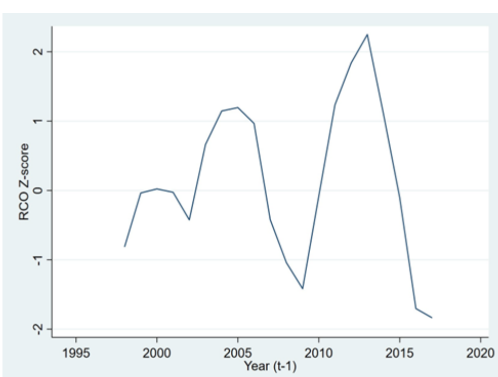
(c) United States (Z-score-based)



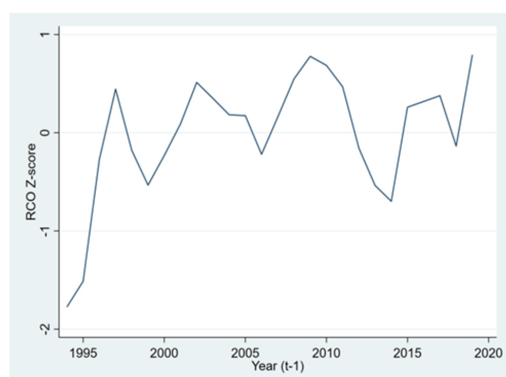
(d) Germany (Z-score-based)



(e) Ireland (Z-score-based)



(f) Spain (Z-score-based)



Appendices

A 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 initially developed by U.S. bank supervisors (Purnanandam, 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:

$$EDF^s_{i,c,t} = \beta_1 CAP^s_{i,c,t} + \beta_2 LLP^s_{i,c,t} + \beta_3 ROA^s_{i,c,t} + \beta_4 CI^s_{i,c,t} + \beta_5 LIQ^s_{i,c,t} + \mu_{c,t} + \epsilon_{i,c,t}$$

Where $EDF^s_{i,c,t}$ is the (log) EDF of bank i, located in country c , in year t. The superindex s denotes that the variables have been standardized to have a mean zero and standard deviation 1 across all observations. The notation for the explanatory variables is analogous. All variables were winsorized at a 1 percent level before being standardized. The parameter 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.[29]

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:

$$SRisk^s_{i,c,t} = \hat{\beta}_1 CAP^s_{i,c,t} + \hat{\beta}_2 LLP^s_{i,c,t} + \hat{\beta}_3 ROA^s_{i,c,t} + \hat{\beta}_4 CI^s_{i,c,t} + \hat{\beta}_5 LIQ^s_{i,c,t}$$

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

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

Table A.1: Synthetic EDF Parameters

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

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 control 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.

B Data

B.1 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 B.2. 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 from Orbis and International Monetary Fund (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) inter-bank 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).[30] 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 evolve.

B.2 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:

1. Select institutions in the FitchConnect universe based on their market sector description and specialization. We keep institutions with the following market sector description: bank holding companies, banks, credit unions, development banks, private banks, retail & consumer banks, trade finance banks, trust & processing banks, universal commercial banks, and 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, cooperative banks, multi-lateral governmental banks,

[30] Code available at: https://sites.google.com/site/dimitriskorobilis/matlab

state/government banks, or savings banks. We drop all other institutions. We drop a handful of institutions that we know are not banks.

2. Drop observations with missing data for total assets.

3. Keep only annual statements.

4. Keep only one statement quality type in this priority order: restated, original, preliminary, and partial.

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

6. Match BVD IDs identifiers (from Orbis) with Fitch IDs identifiers (from Fitch Connect)

7. 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, and regulatory.

8. Match each bank with its global ultimate owner (GUO) in any given year. Historical ownership information from 2007 onward is sourced from the FitchConnect/BvD historical ownership database. Historical ownership information for 1999-2006 is sourced from International Monetary Fund (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 this GUO owned the bank during all previous years.

9. 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.

10. Based on the GUO information, we drop subsidiaries when their GUO is in the same country and the dataset. This is to avoid double counting at the country level. Additionally, we manually drop some banks 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).

11. Identify mergers using Orbis M&A data.

12. Tag bank-years with 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, relative to the bank's recent history and other banks in the country that year.

13. Tag bank-years when there is an accounting system change.
14. Merge the data with CreditEdge data (EDFs).
15. Starting from the cleaned 2021 vintage, we add the bank-years in the 2018 vintage but not in the 2021 vintage.

In our analysis, we exclude bank years associated with a change in consolidation level (step 9), a large merger (step 12), or 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 an 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 checked the robustness of our results in this sample.

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

B.3 Loan-level Dataset Construction

Using Dealogic's global transaction-level syndicated loan database, we construct annual bank-level Leveraged Loan Shares (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 syndicate. 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 banks. 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 participating 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.

Table B.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

Table B.2: 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)	To be added
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

Continued on next page

Table B.2 – continued from previous page

Variable	Description	Source
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 the average riskiness decile of top corporate debt issuers and the 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	To be added	To be added
Systemic Banking Crisis	Dummy variable indicating whether a country is in a systemic banking crisis	Laeven and Valencia (2020)
Banking Sector Stock Returns	To be added	To be added
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

Continued on next page

Table B.2 – continued from previous page

Variable	**Description**	**Source**
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 Credit-Edge
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

Table B.3: 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.

C Extended Version of Paper Tables (all coefficients)

Table C.1: RCO and Growth at Risk: Robustness to Method, Sample, and Measure. All Coefficients

	[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
Panel A: MSS Method									
Real GDP Growth	0.226	0.284	0.336	0.174	0.232***	0.274***	0.158	0.142**	0.127
	(2.698)	(1.149)	(0.275)	(0.136)	(0.081)	(0.104)	(0.102)	(0.067)	(0.095)
Δ(Credit/GDP)	-0.143	-0.064	0.006	-0.155***	-0.103***	-0.065**	-0.140***	-0.144***	-0.147***
	(0.666)	(0.284)	(0.068)	(0.037)	(0.022)	(0.028)	(0.033)	(0.022)	(0.031)
FCI	0.769	0.247	-0.218	0.665**	0.255	-0.043	0.456*	0.353**	0.260
	(5.855)	(2.493)	(0.599)	(0.309)	(0.185)	(0.237)	(0.236)	(0.156)	(0.221)
Global FCI	-0.693	-0.526	-0.377	-1.172***	-0.724***	-0.398	-0.940***	-0.795***	-0.663**
	(6.949)	(2.959)	(0.708)	(0.359)	(0.215)	(0.275)	(0.277)	(0.183)	(0.259)
RCO	-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)
Observations	678	678	678	642	642	642	604	604	604
Panel B: Synthetic EDF									
Real GDP Growth	0.371***	0.369***	0.477***	0.185*	0.320***	0.448***	0.155**	0.222***	0.275***
	(0.104)	(0.070)	(0.076)	(0.098)	(0.062)	(0.093)	(0.073)	(0.052)	(0.082)
Δ(Credit/GDP)	-0.087***	-0.038	0.001	-0.154***	-0.073***	-0.020	-0.125***	-0.096***	-0.083***
	(0.030)	(0.032)	(0.021)	(0.029)	(0.023)	(0.021)	(0.020)	(0.026)	(0.023)
FCI	0.244	0.225	-0.131	0.584**	0.060	-0.208	0.340*	0.214	0.045
	(0.285)	(0.188)	(0.159)	(0.247)	(0.143)	(0.180)	(0.204)	(0.137)	(0.190)
Global FCI	-0.211	-0.603***	-0.403*	-1.037***	-0.377**	-0.228	-0.922***	-0.636***	-0.573**
	(0.317)	(0.224)	(0.221)	(0.297)	(0.158)	(0.215)	(0.208)	(0.161)	(0.238)
RCO	-0.322***	-0.145*	-0.090	-0.292***	-0.209**	-0.186**	-0.234***	-0.282***	-0.143
	(0.124)	(0.081)	(0.084)	(0.094)	(0.082)	(0.079)	(0.064)	(0.074)	(0.088)

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Table C.1 – continued from previous page

	[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
Observations	702			666			628		
Panel C: Restricted Sample									
Real GDP Growth	0.190	0.262***	0.360***	0.011	0.179**	0.273**	0.079	0.072	0.166*
	(0.135)	(0.083)	(0.101)	(0.112)	(0.083)	(0.111)	(0.069)	(0.054)	(0.091)
Δ(Credit/GDP)	-0.067**	-0.039**	0.007	-0.127***	-0.034**	-0.020	-0.116***	-0.068***	-0.029
	(0.029)	(0.019)	(0.021)	(0.023)	(0.017)	(0.020)	(0.016)	(0.020)	(0.029)
FCI	0.380	0.320**	0.074	0.833***	0.218	0.050	0.485***	0.460***	0.091
	(0.244)	(0.157)	(0.191)	(0.255)	(0.189)	(0.197)	(0.163)	(0.158)	(0.227)
Global FCI	-0.348	-0.703***	-0.593**	-1.190***	-0.569***	-0.458*	-1.037***	-0.834***	-0.666**
	(0.296)	(0.190)	(0.283)	(0.305)	(0.206)	(0.236)	(0.180)	(0.174)	(0.281)
RCO	-0.235*	-0.078	0.049	-0.295***	-0.182**	-0.087	-0.217***	-0.145*	-0.184*
	(0.123)	(0.094)	(0.134)	(0.109)	(0.086)	(0.102)	(0.078)	(0.086)	(0.098)
Observations	543			516			486		

Table C.2: Quantile Regressions for Bank Stock Returns. All Coefficients

	(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												
Real GDP Growth	-0.251	-0.345	0.028	2.395*	0.932	0.683	0.381	0.694	1.133	0.635	-0.083	0.606
	(2.463)	(1.974)	(1.160)	(1.258)	(0.768)	(0.739)	(0.879)	(1.388)	(0.731)	(0.546)	(0.559)	(0.935)
Δ(Credit/GDP)	-1.832***	-1.049*	-0.586	-0.841	-1.370***	-1.138***	-1.014***	-1.297**	-1.030***	-0.846***	-1.038***	-1.465***
	(0.451)	(0.606)	(0.498)	(0.608)	(0.318)	(0.295)	(0.268)	(0.549)	(0.230)	(0.303)	(0.246)	(0.306)
FCI	18.732***	12.861***	1.050	-5.175*	7.265***	7.428***	5.318**	1.945	5.453**	5.248***	6.417***	2.076
	(4.293)	(4.185)	(3.197)	(3.089)	(2.743)	(2.087)	(2.403)	(3.161)	(2.308)	(1.946)	(1.737)	(2.577)
Global FCI	-23.335***	-16.507***	-8.507**	-5.084	-11.914***	-11.745***	-14.493***	-18.466***	-11.532***	-11.338***	-12.876***	-15.706***
	(4.547)	(5.309)	(4.275)	(4.356)	(3.520)	(2.398)	(2.526)	(4.697)	(2.689)	(1.944)	(1.854)	(2.598)
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 aggregate banking sector indicators												
Real GDP Growth	0.200	0.233	0.314	1.434	1.390	0.375	0.413	0.790	1.141	0.559	0.029	0.134
	(2.274)	(1.983)	(1.078)	(1.152)	(0.959)	(0.769)	(0.748)	(1.299)	(0.739)	(0.674)	(0.531)	(1.020)
Δ(Credit/GDP)	-2.063***	-1.389**	-0.541	-0.764	-1.427***	-1.116***	-1.034***	-1.234**	-0.961***	-0.794***	-1.089***	-1.325***
	(0.456)	(0.598)	(0.459)	(0.590)	(0.346)	(0.264)	(0.267)	(0.535)	(0.262)	(0.287)	(0.219)	(0.302)
FCI	15.336***	11.194***	0.070	-2.446	8.026***	7.785***	5.706**	1.056	5.602**	4.754**	6.261***	2.285
	(4.366)	(4.054)	(3.300)	(2.837)	(2.648)	(2.048)	(2.322)	(3.166)	(2.363)	(2.019)	(1.829)	(3.018)
Global FCI	-23.888***	-17.992***	-6.821	-4.619	-14.034***	-13.112***	-14.344***	-15.331***	-11.476***	-10.978***	-12.714***	-14.158***
	(4.422)	(5.578)	(4.470)	(3.981)	(3.406)	(2.367)	(2.720)	(5.087)	(2.679)	(2.070)	(2.205)	(3.304)
Leverage Skewness	63.233	17.619	9.821	-41.202	53.902*	26.732	14.800	3.165	15.703	24.114	24.084**	10.192
	(38.769)	(25.826)	(17.475)	(37.416)	(30.530)	(18.533)	(11.945)	(17.219)	(29.721)	(27.662)	(12.010)	(21.235)
Average Riskiness	0.100*	0.098*	-0.035	-0.066*	0.031	0.015	-0.035*	-0.053**	-0.010	0.011	-0.020	-0.053**
	(0.057)	(0.055)	(0.046)	(0.035)	(0.021)	(0.021)	(0.021)	(0.025)	(0.023)	(0.018)	(0.017)	(0.022)
RCO	-3.882*	-2.422	-0.219	0.845	-3.065**	-1.374	-0.787	-1.564	-2.897**	-1.341	-1.664*	-2.888**
	(2.021)	(2.107)	(1.747)	(2.131)	(1.291)	(1.026)	(1.076)	(2.080)	(1.300)	(1.066)	(1.002)	(1.288)
Observations	626				626				592			

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Table C.2 – continued from previous page

	(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
C. Controlling for macro indicators												
Real GDP Growth	-0.380	1.174	1.448	2.674**	1.801**	0.913	1.022	3.128**	1.012	1.219*	1.328*	1.768*
	(2.274)	(2.342)	(1.504)	(1.341)	(0.900)	(0.796)	(1.453)	(1.401)	(0.930)	(0.672)	(0.708)	(0.952)
Δ(Credit/GDP)	-1.301**	-0.933	0.528	0.329	-1.012***	-0.788***	-0.498	-0.373	-0.810***	-0.598**	-0.564**	-0.745**
	(0.628)	(0.704)	(0.541)	(0.538)	(0.362)	(0.302)	(0.318)	(0.465)	(0.220)	(0.247)	(0.224)	(0.332)
FCI	15.786***	13.016***	0.948	-3.770	6.443**	7.884***	4.909*	0.794	4.332**	5.083**	5.955***	1.605
	(5.228)	(4.552)	(2.997)	(3.473)	(3.179)	(2.337)	(2.583)	(2.500)	(2.029)	(2.153)	(1.753)	(2.644)
Global FCI	-39.848***	-27.338**	-16.001	-25.846**	-18.646**	-15.375***	-27.193***	-45.576***	-17.360***	-16.499***	-29.495***	-41.473***
	(10.423)	(11.190)	(13.392)	(10.704)	(8.464)	(5.235)	(9.234)	(5.740)	(6.128)	(5.168)	(5.393)	(5.437)
RCA	-3.488	-6.488**	-8.626***	-5.001*	-5.401***	-5.282***	-4.401**	-6.057***	-1.931	-3.083*	-3.227**	-3.368*
	(3.904)	(3.116)	(3.206)	(2.995)	(1.779)	(1.492)	(2.225)	(2.289)	(2.058)	(1.672)	(1.344)	(1.914)
CA/GDP	-0.418	-1.040	3.274*	3.359*	-0.126	-0.091	3.028**	4.588***	0.056	0.526	1.948**	3.526***
	(1.681)	(1.795)	(1.757)	(1.815)	(1.099)	(0.777)	(1.380)	(1.001)	(0.912)	(0.741)	(0.867)	(1.109)
VIX	-57.892**	-26.392	-25.453	-47.579*	-15.809	-7.363	-34.613	-73.973***	-16.086	-12.545	-43.740***	-72.877***
	(26.780)	(24.681)	(30.910)	(27.380)	(20.476)	(11.967)	(22.155)	(13.630)	(15.019)	(12.740)	(13.782)	(15.073)
DXY	66.282**	24.359	10.438	-14.203	10.960	8.142	6.123	7.619	-0.706	1.971	8.476	41.091**
	(31.567)	(28.078)	(22.195)	(23.599)	(18.554)	(14.030)	(12.725)	(15.706)	(17.507)	(15.392)	(12.255)	(18.155)
DCreditXFCI	0.267	-0.291	0.199	1.069	0.584*	0.405	0.675*	0.954*	0.797***	0.687***	0.522***	0.575
	(0.566)	(0.614)	(0.587)	(0.671)	(0.348)	(0.278)	(0.402)	(0.544)	(0.226)	(0.174)	(0.192)	(0.399)
RCO	-3.799*	-2.840	0.331	-0.120	-2.319*	-1.363	-0.990	-2.162	-1.739	-1.765*	-2.133**	-1.736
	(2.254)	(2.259)	(1.751)	(2.335)	(1.366)	(1.125)	(1.194)	(1.684)	(1.247)	(1.006)	(0.956)	(1.067)
Observations	591	591	591	591	591	591	591	591	560	560	560	560