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## The Riskiness of Credit Allocation and Financial Stability

by Luis Brandão-Marques, Qianying Chen, Claudio Raddatz, Jérôme Vandenbussche, and Peichu Xie



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## The Riskiness of Credit Allocation and Financial Stability

**Prepared by Luis Brandão-Marques, Qianying Chen, Claudio Raddatz, Jérôme Vandenbussche, and Peichu Xie**[1]

Authorized for distribution by Jérôme Vandenbussche

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**Abstract**

We explore empirically how the time-varying allocation of credit across firms with heterogeneous credit quality matters for financial stability outcomes. Using firm-level data for 55 countries over 1991-2016, we show that the riskiness of credit allocation, captured by Greenwood and Hanson (2013)'s ISS indicator, helps predict downside risks to GDP growth and systemic banking crises, two to three years ahead. Our analysis indicates that the riskiness of credit allocation is both a measure of corporate vulnerability and of investor sentiment. Economic forecasters wrongly predict a positive association between the riskiness of credit allocation and future growth, suggesting a flawed expectations process.

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Author's E-Mail Address: LMarques@imf.org; QChen@imf.org; CRaddatz@imf.org; Jvandenbussche@imf.org; PXie@imf.org

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# I. INTRODUCTION

The recent global financial crisis has renewed interest in understanding the role played by credit to the private sector as a source of financial instability. A sizable literature has focused on changes in the aggregate volume of credit and pointed to the dangers of fast credit expansions because they lead to increased leverage in the banking sector and the private nonfinancial sector, making the economy more vulnerable to negative shocks (Schularick and Taylor, 2012).[2] A more recent literature has documented the additional role of credit spreads and shown that low spreads precede episodes of financial instability as they set the stage for large spread reversals and large associated credit losses in financial institutions (Lopez-Salido et al. 2017, Krishnamurthy and Muir, forthcoming).

In this paper, we show that a third dimension of credit to the private sector—the extent to which the distribution of credit is tilted towards riskier borrowers—contains relevant information about future financial stability. To capture this new dimension, we build on work by Greenwood and Hanson (2013) –henceforth GH– who propose an indicator, labeled ISS, measuring the dispersion of firm-level credit quality across buckets of firms sorted by net debt issuance. Since this indicator is related both to borrower default risk and to the cross-sectional distribution of credit flows, we refer to it as the *riskiness of credit allocation*.

It may seem intuitive that a measure that captures the extent to which credit flows correlate with firm credit quality should provide information on future financial stability outcomes. However, this proposition has remained at best a conjecture in the financial stability literature.[3] A small number of recent papers has analyzed the relevance of the distribution of credit across heterogeneous borrowers for excess bond returns (the focus of the GH paper), or GDP growth (Lopez-Salido et al., 2017; Gomes et al., 2018; Kirti 2018), but not on downside risks to GDP growth and the probability of financial crises, which is our area of attention in this paper.

Our contribution is twofold. First, we contribute to the literature on the dynamics of the composition of corporate credit flows by showing that the riskiness of credit allocation has followed a procyclical pattern at the global level over our 25-year-long sample period. We further provide cross-country evidence that ISS is positively associated with contemporaneous GDP growth and change in the credit-to-GDP ratio. This latter association is stronger when domestic financial conditions are looser, when bank lending standards are

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[2] Other empirical studies of financial crisis and financial sector stress documenting the role of changes in aggregate domestic credit volumes or the domestic credit gap include Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), Borio and Lowe (2002), Borio and Drehmann (2009), Gourinchas and Obstfeld (2012), Dell'Ariccia et al. (2016), and Baron and Xiong (2017). Büyükkarabacak and Valev (2010) and Aldaroso et al. (2018) suggest that changes in household debt and in cross-border bank claims are useful credit quantity early warning indicators too.

[3] In the conclusion to their paper, Jiménez et al. (2014) conjectured that "the compositional change in the supply of credit, in particular with respect to risk" was "more important [for financial stability] than the volume of credit."

easier, and when credit spreads are lower, pointing to shifts in credit supply as an important driver of the riskiness of credit allocation. [4]

Our second and main contribution is to the financial stability literature. We show that while the riskiness of credit allocation is not significantly associated with future GDP growth, it helps better predict downside risks to GDP growth and banking crises at horizons of up to three years.[5] This predictive power—which we document based on a large sample of advanced and emerging economies over 1991-2016—is additional to that of changes in credit-to-GDP and of price of risk proxied by a financial conditions index.

We explore two plausible mechanisms for this key result linking the riskiness of credit allocation and financial stability outcomes. We find that variations in ISS, conditional on size of credit expansion and level of financial conditions, captures variations in the size of the weak tail of firms. Recent research has shown that firms' ability to access credit and make investments when financial conditions tighten is related to their degree of financial vulnerability (Duval et al., forthcoming). Therefore a higher level of ISS means greater amplification of negative financial shocks. Second, we find that ISS helps predict reversals of financial conditions and corporate spreads. These two results indicate that ISS combines features of a corporate financial vulnerability measure and of a risk sentiment measure.

Several financial-frictions-based theories are relevant in explaining the relationship between ISS and the size of credit expansions. First, with costly state verification, the availability of credit to high-risk firms follows from their net worth (including collateral values) and is procyclical, generating a financial accelerator effect (Bernanke and Gertler 1989). Second, banks' capacity and incentives to screen borrowers can deteriorate in periods of significant credit expansions, reinforcing the procyclical nature of lending to relatively riskier firms (Berger and Udell 2004; Dell'Ariccia and Marquez 2006). These theories, however, cannot provide a full account of our evidence, as they do not explain why the riskiness of credit allocation helps predict financial stability episodes controlling for the size of the credit expansion, financial conditions, and macroeconomic conditions.

Belief-based theories provide another class of possible explanations. In the narratives of Minsky (1977), Kindleberger (1978) and Bordalo et al. (2018), variations over time in investor beliefs and risk appetite can cause more credit being supplied to riskier firms during periods of optimism and/or neglect of risk. During those times, the composition of the flow of credit does not follow mechanically from aggregate credit volumes and current economic conditions. A further exploration of our data provides additional support for a role played by

[4] Various studies from the mid-1990s for the United States suggest that debt issuer quality is countercyclical (Lang and Nakamura 1995; Bernanke, Gertler, and Gilchrist 1996). More recently, GH offer further evidence of such behavior in the United States during the past few decades. Analyses of granular loan-level data from Spain and the United States also reveal a negative association between the level of short-term interest rates and the probability of extending loans to risky borrowers (Jiménez and others 2014; Dell'Ariccia, Laeven, and Suarez 2017). Acharya et al. (2019) provide evidence of greater lending to risky borrowers after a policy-induced relaxation of financial conditions in the euro area.

[5] This result is reminiscent of Baron and Xiong (2017), who provide cross-country evidence that bank equity investors face greater crash risk but do not obtain higher mean returns during credit expansions.

belief-based explanations. Extending the result obtained by Mian et al. (2017) for aggregate credit volumes, we show that ISS is positively related to the IMF's GDP growth forecast and GDP growth forecast error, indicating a role for flawed expectations.

We submit our key findings to a comprehensive set of robustness checks. Importantly, we show that our results are robust with respect to the way we specify the ISS variable, because different indicators to measure firm-level credit quality may be suitable to different market and data environments. As GH, the ISS indicator we use in our regressions is based on the expected default frequency (EDF). Because its value as a credit risk indicator may be deemed problematic for countries with illiquid equity markets, we also calculate ISS using three common accounting ratios—debt-to-assets (leverage) ratio, interest coverage ratio (ICR), and debt-to-EBITDA ratio. We provide a full set of empirical results for the leverage ratio in the core of the paper, and use the other two ratios to check the robustness of our benchmark results. Overall, we find that our results are similar regardless of the underlying firm vulnerability indicator used to construct ISS. Our key findings are also robust to perturbing various other elements of the definition of ISS, and to using alternative aggregate credit series as well as a large set of controls following the literature on financial crises.

The remainder of the paper is organized as follows. Section II discusses data sources and describes the construction of the two core (EDF-based and leverage-based) ISS indicators. Section III describes their evolution at the global level and in selected countries. Section IV discusses their cyclical properties, and their relationship to indicators of domestic financial conditions. The paper then turns to the empirical analysis of the relationship between the riskiness of credit allocation and downside risks to GDP growth (Section V), and to the occurrence of banking crises (Section VI). Section VII presents robustness checks. Section VIII discusses possible mechanisms linking variations in the riskiness of credit allocation and future financial instability. Section IX concludes and is followed by a data appendix (Appendix A). A second appendix (Appendix B) is available online. It provides additional results and further robustness checks.

## II. CONSTRUCTION OF THE RISKINESS OF CREDIT ALLOCATION AND DATA SOURCES

### A. Construction of the Riskiness of Credit Allocation indicator

We build on GH to construct the ISS indicator for a set of 55 countries (26 advanced economies and 29 emerging markets) at the annual frequency over the 1991–2016 period using firm-level data. These data are sourced from the Worldscope database, which provides a rich set of financial statement variables for listed firms. Appendix A provides details on the country sample and Online Appendix B provides explanations on the data cleaning process. We use only country-years for which observations for at least 40 firms are available to reduce potential volatility associated with a small number of firms as well as firms' entry and exit.

In their analysis, GH use the expected default frequency (EDF) as the preferred firm-level measure of credit quality and demonstrate the robustness of some of their key results to the use of leverage instead. We treat EDF and leverage more symmetrically because the low liquidity of some stock markets outside the largest advanced economies makes the EDF – a market-based measure – less obviously superior as a measure of credit risk in a broad cross-country sample.[6] Therefore, we construct two main ISS measures: $\text{ISS}^{\text{EDF}}$ and $\text{ISS}^{\text{Leverage}}$ and two additional measures based on the interest coverage ratio (ICR), and the debt-to-EBITDA ratio for our robustness analysis.[7]

For each firm-level indicator, ISS is built as follows: First, in each year, each firm is assigned the value (from 1 to 10) of its decile in the distribution of the indicator in the country where it is located. A higher decile represents a larger value of the underlying indicator. Second, firms are similarly sorted by the change in net debt to lagged total assets into five equally-sized buckets. Firms in the bucket with the largest increases in debt (relative to their lagged assets) are called "top issuers," and firms in the bucket with the largest decreases in debt are called the "bottom issuers." A raw ISS measure is computed as the difference between the average vulnerability decile for the top issuers and the corresponding average for the bottom issuers:

$$ISS_{c,t}^{raw,X} = \frac{\sum_{i \in Top\_Issuer\_Quintile} Decile_{i,c,t}^{X}}{N_{c,\,t}^{Top\_Issuer\_Quintile}} - \frac{\sum_{i \in Bottom_{Issuer_{Quintile}}} Decile_{i,c,t}^{X}}{N_{c,t}^{Bottom_{Issuer_{Quintile}}}}, \qquad (1)$$

where $X \in \{EDF, leverage\}$, $Decile^{X}$ is the decile in the distribution of the vulnerability indicator $X$, $N$ is the number of firms, $i$ is the firm, $c$ is the country, and $t$ is the year. The use of deciles abstracts from changes in the mean and shape of the distribution of the credit quality indicator, focusing only on the ranking of a firm in the distribution of that indicator.[8] Because the focus of the paper is on the dynamics of the riskiness of credit allocation within countries and not on its cross-country variation, we normalize this raw measure by subtracting its country-specific mean.[9] This removes any influence of the country-specific sectoral composition of firms and ensures greater cross-country and cross-measure comparability. Since both a higher EDF and higher leverage are indicators of lower credit quality, an increase in ISS signals higher vulnerability. Figure 1 shows the distribution of the

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[6] The construction of the EDF variable is explained in Online Appendix B.

[7] Leverage, ICR, and debt-to-EBITDA all have a strong monotonic relationship with credit ratings (Moody's, 2006).

[8] Using deciles also minimizes the influence of outliers and avoids the possibility of picking up secular trends. A potential downside of transforming into deciles is that information about changes in the cross-sectional dispersion of the indicator is thrown away. The robustness analysis in Section VII shows that our key results hold even when the raw firm-level vulnerability indicators are used to construct ISS.

[9] Krishnamurthy and Muir (forthcoming) also resort to normalization of their credit spread series to enhance cross-country comparability. While it is challenging to establish a "neutral" level for the riskiness of credit allocation, its average over an extended period could be a good proxy.

two indicators, which have the shape of a bell curve and have a standard deviation of about one.

The share of high yield bond issuance (HYS) is an alternative measure of debt issuer quality (Lopez-Salido et al. 2017, Kirti 2018). However, in addition to the reasons provided by GH, we have one important reason to prefer ISS to HYS: [11] bond market development was limited in most advanced economies outside the U.S. until the late-1990's and remains limited in most emerging markets and small advanced economies today. This, in light of the cross-country context of our study, makes HYS a very noisy and unduly volatile indicator.[12]

### B. Other data

Macroeconomic data series, including credit series, are sourced from the International Monetary Fund (IMF)'s International Financial Statistics (IFS) and World Economic Outlook databases, the Bank for International Settlements (BIS), as well as Haver Analytics. Our baseline credit series is that from IMF's International Financial Statistics as it provides the greatest coverage. Financial variables are sourced from Bloomberg and Thomson Reuters. Lending standards are obtained from Haver Analytics. Financial conditions indices are constructed for 43 countries over 1990-2016 as described in Online Appendix B. Data on financial crises are obtained from Laeven and Valencia (2018). The change of the credit-to-GDP ratio is winsorized at the 1 percent level to reduce the influence of outliers. Country coverage is summarized in Appendix Table A1. Further details on data sources and definitions are provided in Appendix Table A2.

## III. The Riskiness of Credit Allocation and Its Evolution Across Countries

The evolution of the riskiness of credit allocation across countries suggests clear global patterns, as shown on Figure 2 which plots the two-year moving average of the two core ISS indicators for the median country. Its dynamic at the global level is broadly the same for $ISS^{EDF}$ and $ISS^{Leverage}$. Starting from elevated levels in the late 1990s, it fell in 2000–04 in the aftermath of the Asian and Russian crises and of the burst of the dot-com equity bubble, reached its historical low in 2002 for $ISS^{EDF}$ and in 2004 for $ISS^{Leverage}$, rose steeply afterwards and hit a peak at the onset of the global financial crisis. It then declined sharply

[11] GH mention three reasons. First, ISS reflects a broader measure of debt issues, including both loan and bond financing. As a result, unlike HYS, ISS is not impacted by secular shifts in the relative sizes of the markets for low-grade bonds and low-grade loans. Second, ISS is not affected by firms' ability or willingness to substitute across bonds and loans. Third, ISS holds constant the definition of firm credit quality, which overcomes the problem of credit ratings standards changing over time. In fact, there is evidence that rating agencies became more conservative in assigning corporate credit ratings over the period 1985 to 2009 (Baghai et al. 2014), and that investment-grade and speculative-grade rating standards diverged between 1985 to 2002 (Alp 2013).

[12] Out of the 55 countries in our sample, only 6 have at least one firm issuing a high-yield bond and one firm issuing an investment-grade bond every year between 1995 and 2016. To partially get around the issue of low bond market development, Kirti (2018) adds corporate and sovereign issuances to construct his high-yield share indicator.

over the next two years and was slightly below its pre-crisis level at the end of 2016, the latest data point in our analysis.

This global dynamic is reflected at the country level, with some country-specific nuances. Figure 3 shows the evolution of $ISS^{EDF}$ and $ISS^{Leverage}$ in six major economies during 1995–2016. The two measures display similar patterns in the six countries.

- The dynamics in the United States (Figure 4, panel 1) and Japan (Figure 4, panel 2) are very similar in both cyclicality and magnitudes.[13] The most recent period (2014–16), however, suggests a divergence: the riskiness of credit allocation decreased in the United States to a relatively low level while in Japan it remained at a level that is relatively high in historical perspective.[14]
- Figure 4, panels 3 and 4 show contrasting developments in two of the largest euro area countries. Spain (Figure 4, panel 3) had a credit boom from the late 1990s to the mid-2000s, which was followed by a deep recession during the global financial crisis and the euro area sovereign debt crisis. Measures of the riskiness of credit allocation for this country reflect these developments quite well: a steep rise in riskiness took place in the mid-to-late 1990s, leading to very high levels of riskiness until the crisis of 2008, which triggered a sudden and large fall of the indicator. This pattern is consistent with findings of Banco de España (2017). By contrast, variations in the riskiness of credit allocation in Germany (Figure 4, panel 4), a country that did not have a credit boom during the 20-year period, have remained within the same narrower range as the United States and Japan, and the measure has moved into positive territory in recent years, suggesting a higher level of risk-taking.
- The evolution of the riskiness of credit allocation in India (Figure 4, panel 5) has broadly followed global patterns, and the measure was at a relatively low level in 2016. The synchronization of China (Figure 4, panel 6) with global developments is weaker—peaks and troughs appear to occur with a two-to-three-year lag. The finding of a peak in 2009–10 is consistent with recent evidence that the implementation of a large stimulus plan beginning at the end of 2008 led to a misallocation of credit (Cong and others 2017).

## IV. The Cyclicality of the Riskiness of Credit Allocation

These patterns raise several questions regarding the cyclicality of the riskiness of credit allocation. Does it systematically comove with GDP growth and credit growth? If so, does the association with credit growth depend on measures of financial conditions that signal

[13] The pattern in the United States closely resembles that shown on Figure 1 in GH. The decline in Japan in the first half of the 2000s is consistent with the findings of Fukuda and Nakamura (2011) in their study of zombie lending.

[14] In the United States, corporate leverage increased across the board during 2010–16. This applies to the median firm as well as to firms with high leverage, and to firms issuing the most debt. However, since we focus on differences across groups of firms, the riskiness of credit allocation does not need to rise. During 2014-16, the average leverage decile of firms issuing the most debt decreased, while the average leverage decile of firms issuing the least debt increased, resulting in a decrease in the riskiness of credit allocation during that period.

expansions in credit supply, such as credit spreads or a broad price-based financial conditions index? We shed light on these questions using standard cross-country panel regressions.

To analyze the dynamics of the composition of corporate credit flows, we estimate the following equation:

$$ISS_{i,t}^{V} = \alpha_i^V + \gamma_t^V + \beta_1^V \Delta GDP_{i,t} + \beta_2^V \Delta Credit_{i,t} + \beta_3^V Control_{i,t} + \varepsilon_{i,t}^V, \qquad (2)$$

in which $V \in \{EDF, leverage\}$ represents a firm-level vulnerability indicator, and correspondingly $ISS_{i,t}^{V}$ represents the riskiness of credit allocation based on indicator $V$ for country $i$ at time $t$. $\Delta GDP$ is real GDP growth, and $\Delta Credit$ is the change in the ratio of bank credit to the nonfinancial private sector to nominal GDP. $Control$ is the domestic currency appreciation against the U.S. dollar, and helps control for a potential mechanical valuation effect on ISS from debt denominated in foreign currency.[15] Both country ($\alpha_i^V$) and year ($\gamma_t^V$) fixed effects are included. The standard errors are clustered at the country level.

Results are provided in Table 1. Whether EDF-based (column (1)) or leverage-based (column (2)), the riskiness of credit allocation increases when GDP growth or changes in the domestic credit-to-GDP ratio are stronger. These findings are consistent with standard financial accelerator mechanisms, and with mechanisms in which credit supply shocks affect macrofinancial outcomes through a risk-taking channel. The association of credit expansion with greater riskiness of credit allocation is statistically significant for both measures. A one standard deviation increase in the change of the credit-to-GDP ratio (equivalent to an increase of 5.5 percentage points) is associated with an increase in the riskiness of credit allocation of 0.12–0.25 standard deviation, depending on the ISS measure.[16] If the specification is enriched by adding a credit boom dummy (constructed as in Dell'Ariccia et al. 2016), a variable capturing the length of a credit boom, or dummies to capture different phases of a credit boom, none of these variables is significant. This points to the absence of nonlinearities in the relationship between the size of a credit expansion and the riskiness of credit allocation, but also that the relationship is not simply driven by extreme episodes of large credit expansions.

While the relationships documented above only establish the cyclical patterns of ISS and do not speak to causality, we can use shed some additional light on the mechanisms behind changes in the riskiness of credit allocation by noting that supply-driven credit expansions are likely to be accompanied by looser financial conditions or looser lending standards. To analyze the relationship between size of credit expansion, financial conditions, and riskiness

[15] A depreciation against the US dollar generates a mechanical positive association between change in net debt and leverage for firms with US dollar-denominated debt. Since we don't have information on the currency composition of firm liabilities, we cannot directly control for it in the construction of net debt flows underlying the ISS measures.

[16] The results are robust (and coefficients only slightly smaller) when instrumenting GDP growth and the change in the credit-to-GDP ratio by their lagged values to account for their potential endogeneity.

of credit allocation, and shed further light on the role of credit supply shifts in the dynamics of ISS, we therefore enrich equation (2) as follows:

$$ISS_{i,t}^{V} = \alpha_i^{V} + \gamma_t^{V} + \beta^{V} Controls_{i,t} + \delta^{V} F_{i,t} + \theta^{V} \times F_{i,t} \times \Delta Credit_{i,t} + \varepsilon_{i,t}^{V}, \qquad (3)$$

in which $Controls_{i,t}$ is a vector of control variables including real GDP growth, change in the credit-to-GDP ratio, and domestic currency appreciation as discussed above. The term $F_{i,t}$ represents either a financial conditions index (FCI), a survey-based measure of bank lending standards, or a corporate credit spread (capturing credit market conditions). Both the change in the credit-to-GDP ratio and the FCI are demeaned at the country level, while lending standards and corporate spreads are transformed into a z-score to ensure greater cross-country comparability. The estimated coefficient $\hat{\theta}^{V}$ captures the marginal effect on the credit cyclicality of the riskiness of credit allocation of a change in the financial conditions variable. The standard errors are clustered at the country level, as before.

Table 2 reports the results. The association between larger credit expansions and riskier allocations is stronger when the price of risk is low (columns 1 and 4), when lending standards are loose (columns 2 and 5), or when corporate credit spreads are low (columns 3 and 6), indicating that outward credit supply shifts are associated with riskier allocations. To capture a possible effect of search for yield motives (Rajan, 2005), we also examined a possible role for the long-term rate, either transformed into a z-score or a dummy indicating a value in the lowest quartile of the country-specific distribution. While the sign of the coefficients indicates an association between lower long-term rates and higher riskiness of credit allocation that is consistent with a search for yield motive, their statistical significance is weak.

## V. THE RISKINESS OF CREDIT ALLOCATION AND DOWNSIDE RISKS TO GROWTH

We move on to ask whether the riskiness of credit allocation helps predict future GDP growth. One might expect that a relatively larger expansion of credit to riskier firms would have benefits for future economic activity if these firms were previously credit-constrained and were now able to boost their investment to seize growth opportunities. To investigate this possibility, we estimate the following equation:

$$\Delta y_{i,t,t+h} = \alpha_i^{V} + \gamma_t^{V} + \beta \Delta \left(\frac{Credit}{GDP}\right)_{i,t-1}^{mv3} + \delta FCI_{i,t-1}^{mv3} + \theta ISS_{i,t-1}^{V,mv3} + \mu Controls_{i,t-1}^{mv3} + u_{i,t}, \qquad (4)$$

in which $\Delta y_{i,t,t+h}$ is cumulative real GDP growth rate from *t* to *t*+*h*, where *h*=1,2,3. The change of the credit to GDP ratio, FCI, and ISS are the same as in the previous section. The choice to include the FCI instead of the corporate spread as a measure of the price of risk is dictated by the smaller availability of the latter. Both country ($\alpha_i^{V}$) and year ($\gamma_t^{V}$) fixed effects are included. Controls include real GDP growth. All explanatory variables enter the equation as the first lag of their simple three-year moving average.

Results, provided in Table 3, indicate that although credit expansions and tight financial conditions tend to forecast future GDP declines, as already documented in the literature, the relationship between ISS and future GDP growth is never positive and rarely significant. This suggests that a riskier credit allocation does not provide any extra kick to future GDP growth.[17]

This insignificant relationship, however, may mask heterogeneity across different parts of the future GDP growth distribution. In the spirit of Adrian et al. (2018), who show that the distribution of GDP growth evolves over time as a function of economic and financial conditions, we re-examine these results using quantile regressions. To do so, we replace the left-hand-side of Equation (44) by $\Delta y^{d}_{i,t,t+h}$, where $d$ represents a decile, and use Powell (2016)'s fixed effect quantile panel estimator for each decile of the 3-year cumulative GDP growth distribution.[18]

Columns (1) through (9) of Table 4 show the results for individual deciles. They reveal that a greater riskiness of credit allocation shifts the whole left tail and the median – in other words, the bottom five deciles– of the growth distribution to the left, and that it moves the top deciles to the right, although generally not significantly so. In other words, the riskiness of credit allocation has a significant impact on downside risks to growth.

Our findings indicate that a riskier credit allocation does not result in a trade-off between greater mean growth and greater downside risks to growth. Instead, it increases downside risks without a clear impact on average growth nor in the upper tail of the future GDP growth distribution. This has some similarity with the findings of Baron and Xiong (2017), which document that strong banking sector credit growth is associated with both a greater likelihood of bank equity price crash and lower mean equity returns, indicating a neglect of crash risk.

In Table 5, we zoom in on the bottom two deciles of the 1-year, 2-year, and 3-year ahead GDP growth distributions. Variations of the riskiness of credit allocation appear strongly related to movements of the left tail of the growth distribution over all horizons. Panel A in the top half of the table shows the results obtained with $ISS^{EDF}$, while Panel B at the bottom shows the results obtained with $ISS^{Leverage}$. The change in credit-to-GDP is always has a negative and significant effect. The coefficient for the FCI is positive and is significant mostly in the first year. The EDF-based riskiness of credit allocation is negative and significant for both deciles over two- and three-year horizons, but only for the second decile

[17] We note in passing that negative coefficients for the change in credit to GDP ratio are consistent with findings by Mian et al. (2017).

[18] The Powell (2016) estimator features nonadditive fixed effects and is appropriate for our setting where N is larger than T.

during the first year, while the leverage-based riskiness of credit allocation is always negative and significant. In quantitative terms, an increase in the riskiness of credit allocation by one standard deviation shifts the left tail of the 3-year cumulative growth distribution to the left by 1-1.3 percentage point for the EDF-based measure and by 0.6-0.7 percentage point for the leverage-based measure.

## VI. THE RISKINESS OF CREDIT ALLOCATION AND THE OCCURRENCE OF BANKING CRISES

Having shown that the riskiness of credit allocation has a strong effect on the left tail of the future growth distribution, we now revisit the more classic literature on the occurrence of banking crises by augmenting the literature's typical specification with the riskiness of credit allocation as an additional explanatory variable. In other words, using cross-country logit regressions, we analyze whether ISS constitutes an early warning indicator of a systemic financial crisis.

Before turning to the formal econometric analysis, it is worthwhile looking at Panel 1 of Figure 4, which illustrates that the riskiness of credit allocation has a very clear inverted-U shape around systemic financial crisis episodes: it rises gradually during the five years preceding the crisis, reaches a relatively high level, and then falls following the onset of the crisis. In our data, credit expansions are also large before a crisis (Panel 2), which is consistent with findings by Schularick and Taylor (2012), and corporate spreads are low (Panel 3), which is consistent with findings by Krishnamurthy and Muir (forthcoming). By contrast, conventional corporate vulnerability indicators (Panel 4) pick up significantly only when the crisis has already struck.

We analyze the logarithm of the odds ratio of the start of a systemic banking crisis using the following conditional fixed-effects logistic regression model:

$$log\frac{P\left[Crisisstart_t = 1|X_{i,t-1}\right]}{P\left[Crisisstart_t = 0|X_{i,t-1}\right]} = \alpha_i + \beta\Delta Credit_{i,t-1}^{mv3} + \gamma FCI_{i,t-1}^{mv3} + \delta ISS_{i,t-1}^{V,mv3} + \mu Controls_{i,t-1}^{mv3} + u_{i,t} \quad (5)$$

in which *Crisisstart* is a dummy variable equal to 1 at the start of a systemic banking crisis and equal to 0 otherwise, $X$ refers to the vector of explanatory variables, $\alpha_i$ is a country fixed effect, $\Delta Credit$ is the change of the ratio of bank credit to the nonfinancial private sector to nominal GDP, *FCI* is the financial conditions index, $ISS$ is the riskiness of credit allocation, and $V \in \{EDF, leverage\}$. *Controls* includes controls for the macroeconomic environment, namely the change in the current-account-balance-to-GDP ratio and real GDP growth, as in Jordà, Schularick, and Taylor (2016a).[19]. All explanatory variables enter the equation as the first lag of their simple three-year moving average (hence the *mv3* superscript) and are de-

[19] Our specification only differs from Jordà, Schularick, and Taylor (2016a) in that it uses real GDP growth instead of real GDP growth per capita. The results are robust to using real GDP growth per capita.

meaned at the country level. Standard errors are clustered at the country level.[20] Because country fixed effects are included, the regression sample shrinks to include only countries that have had at least one crisis.[21]

Regression results are reported in Table 6. Column (1) shows that changes in the credit-to-GDP ratio predict crises, in line with the bulk of the literature, most notably Schularick and Taylor (2012). Column (2) shows that the price of risk also predicts crises. However, when the change in credit-to-GDP and the price of risk enter the regression together in Column (3), the change in credit-to-GDP ratio ceases to be significant.

Columns (4) to (6) show our key results when ISS is added to the specification. The riskiness of credit allocation is significant when it enters separately (column (4)), together with the change in credit-to-GDP (column (5)), and together with change in credit-to-GDP and price of risk combined (column (6)). Thus, for a given size of credit expansion and a given level of the price of risk, a greater level of the riskiness of credit allocation implies a higher probability of financial crisis. A one standard deviation rise in the ISS measure increases the odds of a crisis by a factor of about four. Comparing columns (3) and (6), one can observe that the Pseudo-R2 shows a sizable improvement when the riskiness of credit allocation is added to the regression.

Conditional fixed effects logit is known to give consistent estimates (Chamberlain, 1980) but does not provide estimates of the individual fixed effects, which are needed if one wants to compute statistics such as the area under the ROC curve (AUROC) which are often found in the literature to assess the performance of a logistic regression model. The unconditional-with-dummies estimator provides estimates of the individual fixed effects but leads to inconsistent estimates due to the incidental parameter problem, although Coupé (2005) finds that the bias is small when T is large.[22] Online Appendix Table B2 shows that coefficients obtained from an unconditional-with-dummies estimator are close to those obtained using the conditional estimator, and that the addition of the riskiness of credit allocation variable to the regression specification boosts the AUROC statistics in this model.

## VII. Robustness analysis

In this section, we present evidence that our main findings are robust: they hold regardless of the choice of the specific credit series and of the choice of firm-level vulnerability indicator, and they are not sensitive to perturbations of the ISS definition.

### A. Alternative aggregate credit series

Our baseline credit series is credit to the private nonfinancial sector provided by domestic banks, as in Schularick and Taylor (2012), Gourinchas and Obstfeld (2012), and Baron and

[20] The results are robust to using two-way-clustering.

[21] Because of the small sample size, we do not report results of regressions where corporate spreads are used instead of the financial conditions index. Nonetheless, results are qualitatively similar, though less significant.

[22] Schularick and Taylor (2012 use conditional fixed effects logit, and their average T is about 90.

Xiong (2017). It is sourced from IFS and has the best country-year coverage. Results for the downside risks to growth model (second decile, 3-yar horizon) using these series are repeated in Column (1) of Table 7a. A broader concept of credit, i.e. total credit provided to the private non-financial sector by *all sectors* (both domestic and foreign), both bank and nonbank) is used in Column (2). These data series are sourced from the BIS. Since the recent literature (Jordà et al 2016, Mian et al 2017, Aldasoro et al. 2018, Alter et al. 2018) has emphasized the role that credit to household plays in overall financial vulnerability,we also split the total credit series by source: results for credit by domestic banks are shown in Column (5), and results for credit by cross-border sources are shown in Column (6). Aldaroso et al.(2018) also find that cross-border claims on banks and nonbanks is a predictor of banking crises, so in Column (7) and Column (8), we use cross-border claims on banks, and cross-border claims on banks plus non-banks. In Column (9), we focus on the credit gap, constructed with the IFS credit data, as Borio et al. (2011) suggest that this indicator a high signal-to-noise ratio to forecast episodes of financial instability.[23]

Panel A at the top of Table 8a provides results for $ISS^{Leverage}$, and Panel B at the bottom provides results for $ISS^{EDF}$. Results are very stable across columns and panels. ISS and the credit quantity variable are always significant, while the FCI is generally insignificant.

Similar robustness exercises for the crisis model are shown in Panel A and Panel B of Table 7b. Results are very stable across columns and panels. Change in credit-to-GDP is rarely significant, while ISS and FCI are always significant.

## B. Alternative firm-level vulnerability indicators

Our baseline firm-level indicators are the expected default frequency and the ratio of debt to assets. We examine the results obtained with two alternative vulnerability indicators sometimes used in the literature, the interest coverage ratio (ICR), and the debt-to-EBITDA ratio. Table 8a shows the results obtained in the downside risks to growth model, while Table 8b shows the results obtained in the crisis occurrence model. Results are very similar to those obtained with the two core vulnerability indicators: ISS is always significant in the crisis model and is associated to shifts in the left tail of the future GDP growth distribution, although more significantly so for the ICR indicator.

## C. Alternative constructions of the riskiness of credit allocation

To provide further evidence that the composition of credit matters to financial stability outcomes, we explore seven perturbations of the construction of the riskiness of credit allocation variable:

[23] The credit gap is the difference between the credit-to-GDP ratio and its long-run trend based on a one-sided HP filter.

- First, we use the raw vulnerability measure (instead of its decile) in the ISS formula, as Gomes et al. (2018) do for the United States.
- Second, we keep the deciles, but weigh them by debt instead of taking their simple average. Firms with relatively larger debt will therefore have a greater impact in this version.
- Third, we sort firms by net issuance in US dollars (instead of net issuance normalized by lagged assets). Large firms will have a greater influence on this version of the measure.
- Fourth, we sort firms by their level of vulnerability (instead of their net issuance to lagged assets) and use deciles of net issuance to lagged assets (instead of deciles of vulnerability). This is a "reverse" ISS.
- Fifth, we combine the first and the third perturbation, i.e. we sort firms by net issuance in US dollars and we use the raw vulnerability measure.

The coefficients of interest for the downside risks to growth model are shown in Table 9a, and in Table 9b for the crisis prediction model. All five alternatives of ISS based on EDF have the right sign and are significant, and four out of five alternatives of the ISS based on leverage have the right sign and are significant (the second alternative is not significant), .

### D. Other robustness checks

Online Appendix B provides additional results of and further robustness checks. We show that the results for the crisis model hold when including including individual lags of ISS (instead of its moving average), and when excluding three years post crisis so as to avoid the post-crisis bias discussed in Bussière and Fratscher (2006). Results in the downside risks to growth model are robust to using GDP per capita. Results of both models are both robust to the inclusion of other early warning indicators identified in the crisis literature are controlled for, including real effective exchange rate and foreign exchange reserves (as Gourinchas and Obstfeld, 2012) or aggregate corporate vulnerability indicators (as Lee et al., 2018).

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## VIII. Discussion of possible mechanisms

We have provided strong evidence of a positive association between the riskiness of credit allocation and both future downside risks to GDP growth and the probability of financial crisis. In this section we explore two mechanisms that could plausibly explain these associations.

First, the riskiness of credit allocation is likely to at least partially capture variations in lending standards to the corporate sector, and therefore the extent to which the most vulnerable firms accumulate further debt, thereby becoming even more vulnerable. Recent research suggests that higher firm vulnerability leads to lower access to credit and lower investment when financial conditions tighten (Duval et al., forthcoming). If it led to a fatter tail of vulnerable firms, a higher level of the riskiness of credit allocation would then amplify the effect of a negative shock on investment and economic activity. To check whether this meachanism is at play, we run the following regression:

$$\Delta Share_{i,t}^{HV} = \alpha_i + \beta\Delta\left(\frac{Credit}{GDP}\right)_{i,t} + \gamma FCI_{i,t} + \delta ISS_{i,t}^{V} + u_{i,t} \qquad (6)$$

where $Share^{HV}$ is the share of assets in high vulnerability firms, and $V \in \{EDF, leverage\}$ as above.[24]

Table 10 presents the results. High vulnerability firms are defined alternatively as those with a leverage ratio above the 75$^{th}$ percentile of their country-specific distribution (columns (1) and (4)), those with an ICR below the 25$^{th}$ percentile of their country-specific distribution (columns (2) and (5)), and those with a debt-to-EBITDA ratio above the 75$^{th}$ percentile of their country-specific distribution (columns (3) and (6)). The regression results confirm that this mechanism plays a role. Regardless of the ISS indicator and the high vulnerability measure used, the coefficient of ISS is very significant, which indicates that changes in ISS capture changes in the distribution of corporate vulnerabilities.

Second, the riskiness of credit allocation could capture a dimension of investor sentiment that is not captured either by the financial conditions index of the change in credit-to-GDP. If so, it should help predict reversals of financial conditions and/or corporate spreads. We thus follow Lopez-Salido et al. (2017) and estimate:

$$\Delta F_{i,t} = \alpha_i + \beta\Delta\left(\frac{Credit}{GDP}\right)_{i,t-1}^{mv3} + \gamma F_{i,t-1}^{mv3} + \delta ISS_{i,t-1}^{V,mv3} + u_{i,t}, \qquad (7)$$

where $F$ is either the financial conditions index or the corporate spread, and $\Delta F$ is its first difference.

Table 11 presents evidence that the riskiness of credit allocation indeed helps predict reversals in financial conditions (columns (1)-(4)) and the corporate spread (columns (5)-(8)). For the reversal in financial conditions, the effect is more than twice stronger when financial conditions are loose (columns (2) and (4)). The riskiness of credit allocation therefore has features of a risk sentiment indicator.

We conclude this discussion by asking in the spirit of Mian et al. (2017) whether there could be a role for behavioral biases in explaining the negative relationship between riskiness of credit allocation and downside risks to future growth. While this question is difficult to answer in the absence of data on expectations of downside risks to growth, one can nevertheless approach it by examining data on GDP growth forecasts. We thus ask whether professional economic forecasts –specifically, the IMF's World Economic Outlook (WEO) forecasts– properly capture the relationship between ISS and future GDP growth documented in Table 3 and discussed in Section V above. To that effect, we estimate versions of Equation (5) where the dependent variable is forecasted GDP growth or the GDP growth forcast error.

[24] Since the ISS measure captures the relative vulnerability of firms that are issuing relatively more debt, there is not mechanical relationship with a higher share of assets in vulnerable firms. ISS may increase because top debt issuers become relatively weaker, even if they remain of better quality than the bottom issuers. Conversely, it may also increase if lower credit quality firms contract their borrowing.

Results are presented in Table 12. Columns (1) and (4) reproduce the results obtained for 3-year ahead cumulative growth. Columns (2) and (5) show that when ISS is high, professional forecasters are also mistakenly anticipating higher GDP growth in the future. Column (3) and (6) then show that the forecast error is positive, significant, and quantitatively large, with a one standard deviation increase in ISS being associated with a forecast error greater that 0.5 percentage points. This result seems difficult to reconcile with a rational expectations-based model, and suggests that economic agents fail to understand the some of the negative effects (such as an increase in downside risks to growth) of an increase in the riskiness of credit allocation.

## IX. Conclusion

In the conclusion to their paper, Greenwood and Hanson (2013) extrapolate their results obtained in the context of the U.S. corporate bond market and suggest that to identify the existence of a sentiment-driven credit boom and implement countercyclical credit policy "[…] looking at credit quantities or credit spreads is not enough - policy makers should also consider the credit quality of debt market financing". In this paper, we show that their ISS measure of debt issuer quality, which we refer to as the riskiness of credit allocation, helps predict shifts in the left tail of the GDP growth distribution as well as systemic banking crises 2 to 3 years ahead in a sample of 55 countries covering the 1991-2016 period. We show that this predictive power of riskiness of credit allocation is additional to that of changes in aggregate credit quantities and that of the price of risk typically emphasized in the financial stability literature. Further, we provide evidence that shifts in credit supply play a role in explaining variations in the riskiness of credit allocation, that these variations are associated with variations in the thickness of the weak tail of the distribution of corporate vulnerability measures, and with future reversals of financial conditions. We also show that economic forecasters wrongly associate increases in ISS with increases in future GDP growth.

Our analysis has implications for macroprudential policy-makers. The calibration of the countercyclical capital buffer currently gives a prominent role to the quantity of aggregate credit and the so-called credit-gap. Our findings suggest that policy-makers also need to take the riskiness of credit allocation into account when seeking to prevent financial instability episodes and to differentiate good credit booms from bad credit booms.

Our findings on the dynamics of the composition of corporate credit flows and on the mistaken perception that riskiness of credit allocation and future GDP growth are positively associated also have implications for theoretical models of credit expansions. They favor models that emphasize credit supply shocks and where behavioral biases play an important role.

We established the predictive performance of the riskiness of credit allocation in sample. Although Appendix Table B8 provides evidence of ISS's predictive power for downside risks to growth in the pre-2008 sample too, reducing concerns that ISS captures only developments around the Great Recession, it would be interesting to establish ISS's out-of-sample performance. This would require longer series, or series at a higher frequency, and is left for future research.

## X. References


Acharya, Viral V., Tim Eisert, Christian Eufinger, and Christian W. Hirsch. 2019. "Whatever It Takes: The Real Effects of Unconventional Monetary Policy.", The Review of Financial Studies, in print.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." *American Economic Review*.

Adrian, Tobias, Federico Grinberg, Nellie Liang, and Sheheryar Malik. 2018. "The Term Structure of Growth-at-Risk", IMF Working Paper 18/180.

Aldasoro, Iñaki, Claudio Borio, and Mathias Drehmann. 2018. "Early Warning Indicators of Banking Crises: Expanding the Family." BIS Quarterly Review, March: 29–45.

Alp, Aysun. 2013. "Structural Shifts in Credit Rating Standards", Journal of Finance, 68(6), December, pp 2435-2470.

Alter, Adrian, Alan Xiaochen Feng, and Nico Valckx, "Understanding the Macro-Financial Effects of Household Debt: A Global Perspective", IMF Working Paper 18/76

Baghai, Ramin P., Henri Servaes, and Ane Tamayo. 2014. "Have Rating Agencies Become More Conservative? Implications for Capital Structure and Debt Pricing", Journal of Finance, 69(5), October, pp 1961-2005.

Banco de España. 2017. "Financing and Investment Decisions of Spanish Non-Financial Corporations." 2016 Annual Report.

Baron, Matthew, and Wei Xiong. 2017. "Credit Expansion and Neglected Crash Risk." Quarterly Journal of Economics 132 (2): 713–64.

Berger, Allen N., and Gregory F. Udell. 2004. "The Institutional Memory Hypothesis and the Procyclicality of Bank Lending Behavior." Journal of Financial Intermediation 13 (4): 458–95.

Bernanke, Ben S., and Mark Gertler. 1989. "Agency Costs, Net Worth and Business Fluctuations." American Economic Review 79 (1): 14–31.

———, and Simon Gilchrist. 1996. "The Flight to Quality and the Financial Accelerator." Review of Economics and Statistics 78 (1): 1–15.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2018. "Diagnostic Expectations and Credit Cycles." Journal of Finance, published online.

Borio, Claudio, and Philip Lowe. 2002. "Assessing the Risk of Banking Crises." BIS Quarterly Review, December: 43–54.

Borio, Claudio, and Mathias Drehmann. 2009. “Assessing the Risk of Banking Crises - Revisited.” BIS Quarterly Review, March: 29–46.

Borio, Claudio, Mathias Drehmann, and Kostas Tsatsaronis (2011). “Anchoring countercyclical Capital Buffers: The role of Credit Aggregates,” *International Journal of Central Banking* 7(4), 189-240.

Bussière, Matthieu, and Marcel Fratzscher. 2006. “Towards a New Early Warning System of Financial Crises”, Journal of International Money and Finance, 25(6), 953-973

Büyükkarabacak, Berrak, Valev, Neven T., 2010. “The role of household and business credit in banking crises”. Journal of Banking and Finance, 34 (6), 1247–1256

Chamberlain, Gary. 1980. “Analysis of Covariance with Qualitative Data.” Review of Economic Studies 47: 225-238

Coupé, Tom. 2005, “Bias in Conditional and Unconditional Fixed Effects Logit Estimation: A Correction”, Political Analysis, 13: 292-295.

Dell’Ariccia, Giovanni, Deniz Igan, Luc Laeven, and Hui Tong. 2016. "Credit Booms and Macrofinancial Stability." *Economic Policy* 31 (86): 299–355.

Dell’Ariccia, Giovanni, Luc Laeven, and Robert Marquez. 2014. "Real Interest Rates, Leverage, and Bank Risk-Taking." *Journal of Economic Theory* 149 (1): 65–99.

Dell'Ariccia, Giovanni, Luc Laeven, and Gustavo A. Suarez. 2017. "Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States." *Journal of Finance* 72 (2): 613–54.

Dell'Ariccia, Giovanni, and Robert Marquez. 2006. "Lending Booms and Lending Standards." *Journal of Finance* 61 (5): 2511–46.

Demirgüç-Kunt, Asli, and Enrica Detragiache, 1998. “The determinants of banking crises in developing and developed countries.” *IMF Staff Papers* Vol. 45(1): 81-109.

Duval, Romain, Hong Gee Hee, and Yannick Timmer (forthcoming), *Review of Financial Studies*.

Fukuda, Shin-ichi, and Jun-ichi Nakamura. 2011. "Why Did ‘Zombie’ Firms Recover in Japan?" *World Economy* 34 (7): 1124–37.

Gomes, Joao F., Marco Grotteria, and Jessica A. Wachter. 2018. “Cyclical Dispersion in Expected Defaults”, *Review of Financial Studies*, no. 4: 1275-1308.

Gourinchas, Pierre-Olivier, and Maurice Obstfeld. 2012. "Stories of the Twentieth Century for the Twenty-First." *American Economic Journal: Macroeconomics* 4 (1): 226–65.

Greenwood, Robin, and Samuel G. Hanson. 2013. "Issuer Quality and Corporate Bond Returns." *Review of Financial Studies* 26 (6): 1483–525.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina. 2014. “Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?” Econometrica 82 (2): 463–505.

Jordà, Òscar, Bjorn Richter, Moritz Schularick, and Alan M. Taylor. 2017. "Bank Capital Redux: Solvency, Liquidity, and Crisis" NBER Working Paper #23287.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2011. "Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons" IMF Economic Review 59 (2): 340–378.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2016a. "The Great Mortgaging: Housing Finance, Crises and Business Cycles." Economic Policy 31 (85): 107–52.

———. 2016b. “Sovereigns versus Banks: Credit, Crises, and Consequences.” Journal of the European Economic Association 14 (1): 45–79.

Kaminsky, Graciela L., and Carmen M. Reinhart. 1999. “The twin crises: the causes of banking and balance-of-payments problems.” *American Economic Review* 89(3): 473-500.

Kindleberger, Charles Poor. 1978. *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Basic Books.

Kirti, Divya. 2018. “Lending Standards and Output Growth.” IMF Working Paper 18/23, International Monetary Fund, Washington, DC.

Krishnamurthy, Arvind, and Tyler Muir. 2017. “How Credit Cycles across a Financial Crisis.” NBER Working Paper 23850, National Bureau of Economic Research, Cambridge, MA.

Laeven, Luc, and Fabian Valencia. 2018. "Systemic Banking Crises Revisited" IMF Working Paper 18/206, International Monetary Fund, Washington, DC.

Lang, William W., and Leonard I. Nakamura. 1995. "‘Flight to Quality’ in Banking and Economic Activity." Journal of Monetary Economics 36 (1): 145–64.

Lee, Seung Jung, Kelly E. Posenau, and Viktors Stebunovs. 2018. “The Anatomy of Financial Vulnerabilities and Banking Crises”, Journal of Banking and Finance, in press.

López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek. 2017."Credit-Market Sentiment and the Business Cycle." Quarterly Journal of Economics 3 (1): 1373–426.

Mian, Atif, Amir Sufi, and Emil Verner. 2017. "Household debt and business cycles worldwide." The Quarterly Journal of Economics 132 (4): 1755-1817.

Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." Journal of Finance 29 (2): 449–70.

Minsky, Hyman P. 1977. "The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to 'Standard' Theory." Challenge 20 (1): 20–27.

———. 1986. Stabilizing an Unstable Economy. New Haven, CT: Yale University Press.

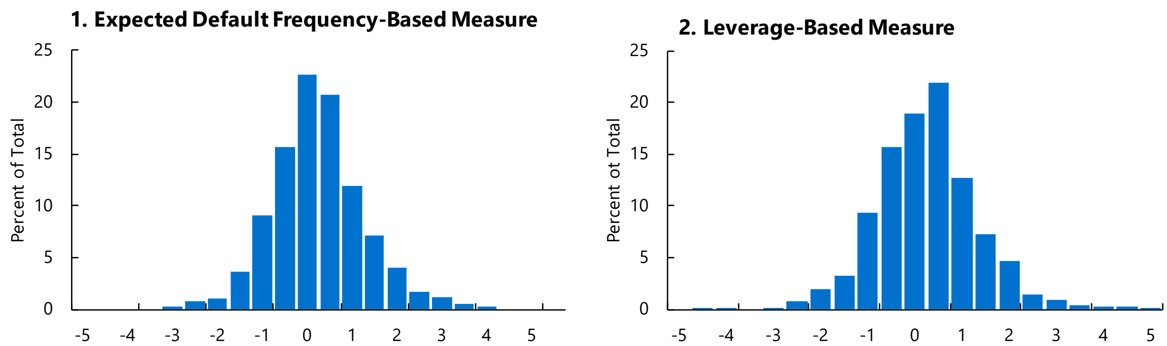
Moody's. 2006. "The Distribution of Common Financial Ratios by Rating and Industry for North American Non-Financial Corporations: July 2006." Special Comment.

Powell, David. 2016. "Quantile Regression with Nonadditive Fixed Effects", working paper.

Rajan, Raghuram G. 2006. "Has Finance Made the World Riskier?" European Financial Management 12 (4): 499–533.

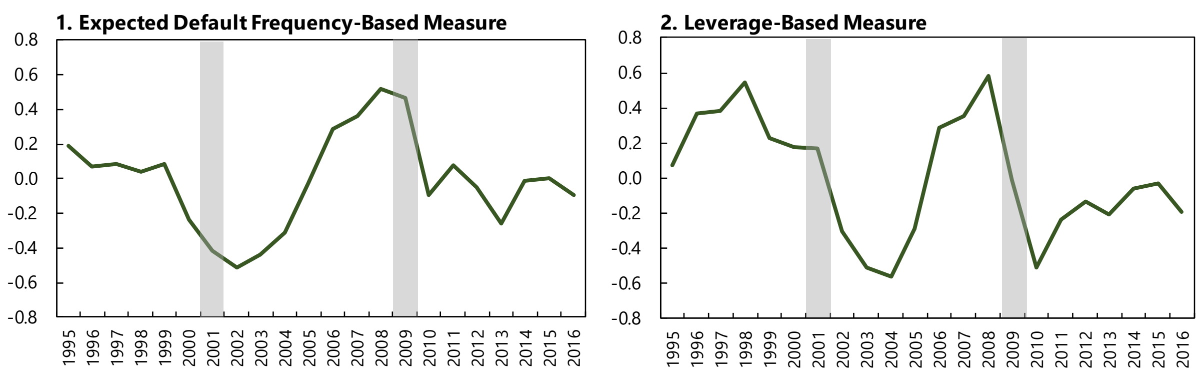
Schularick, Moritz, and Alan M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008." *American Economic Review* 102 (2): 1029–61.

**Figure 1: Riskiness of Credit Allocation Histograms**



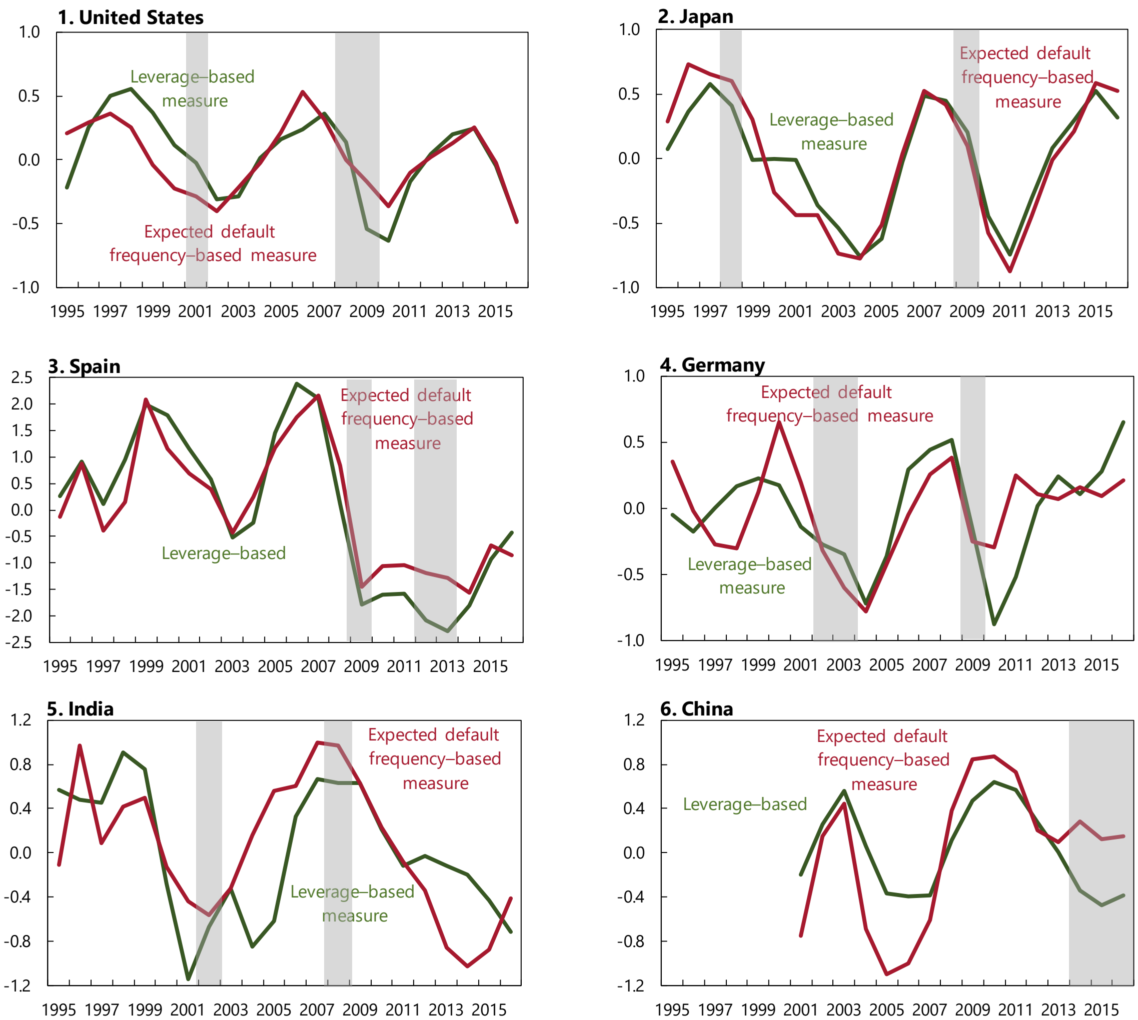

Sources: Worldscope; and authors' estimates.
Note: The value of the riskiness of credit allocation is shown on the x-axis.

**Figure 2: The Riskiness of Credit Allocation at the Global Level**
(Index; global median)



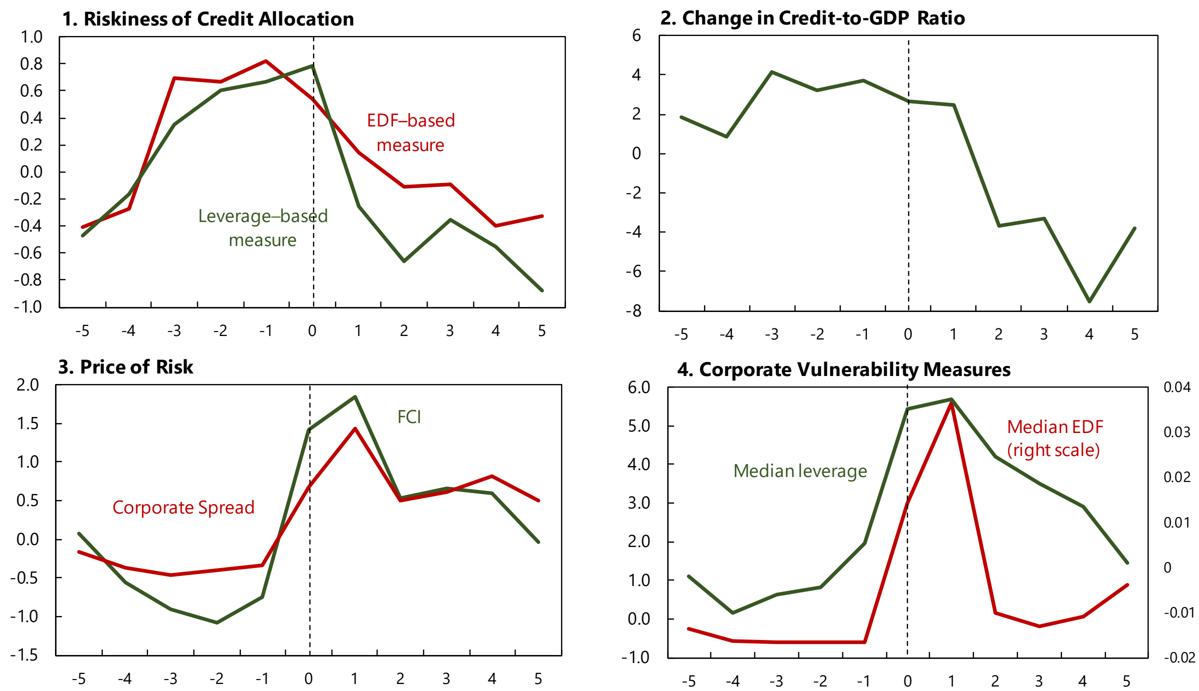

Sources: Worldscope; and authors' estimates.
Note: The panels show the simple two-year moving average of the median country in the (unbalanced) sample. Shaded areas indicate the periods during which annual global real GDP growth was less than 2.5 percent. See Appendix A for country coverage.

**Figure 3. Selected Economies: Riskiness of Credit Allocation, 1995–2016**




Sources: Worldscope; and authors' estimates.
Note: The panels show the simple two-year moving average. Shaded areas indicate periods of growth below the 15th percentile of the country-specific growth distribution.

**Figure 4. Dynamics of the Riskiness of Credit Allocation Around a Crisis Year**
(Index; median across all crisis episodes; 11-year window)




Sources: Laeven and Valencia (2018); Worldscope; and IMF staff estimates.
Note: Systemic banking crises are defined as in Laeven and Valencia (2018). The crisis occurs at time 0. Data series are de-meaned at the country level. The panels show the median across all crisis countries in a balanced panel. In panel 4, median EDF (resp. leverage) refers to the median of the firm-level EDF (resp. leverage) indicator.

**Table 1. Cyclicality of the Riskiness of Credit Allocation**

| | (1) | (2) |
|---|---|---|
| | Dependent Variable: | |
| | $ISS^{EDF}$ | $ISS^{Leverage}$ |
| Real GDP Growth | 0.08*** | 0.08*** |
| | (0.02) | (0.02) |
| Δ(Credit-to-GDP Ratio) | 0.02*** | 0.05*** |
| | (0.01) | (0.01) |
| Appreciation against the US dollar | -0.01 | -0.04*** |
| | (0.01) | (0.01) |
| Number of Observations | 936 | 986 |
| Number of Countries | 53 | 55 |
| $R^2$ | 0.15 | 0.31 |

Source: Authors' estimates
Notes: All regressions are OLS and include country and time fixed effects. Standard errors are clustered at the country level and shown in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

**Table 2. Credit Expansion, Financial Conditions, and Riskiness of Credit Allocation**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent Variable: Riskiness of Credit Allocation Based on EDF | | | Dependent Variable: Riskiness of Credit Allocation Based on | | |
| Δ(Credit-to-GDP Ratio) | 0.04*** | 0.03*** | 0.03*** | 0.05*** | 0.05*** | 0.05*** |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.01) | (0.01) |
| Financial Conditions Index (FCI) | -0.11 | | | -0.12 | | |
| | (0.12) | | | -0.08 | | |
| Δ(Credit-to-GDP Ratio) x FCI | -0.01** | | | -0.01** | | |
| | (0.01) | | | (0.00) | | |
| Bank Lending Standards | | -0.11 | | | -0.10 | |
| | | (0.07) | | | (0.07) | |
| Δ(Credit-to-GDP Ratio) x Bank Lending Standards | | -0.04*** | | | -0.03* | |
| | | (0.01) | | | (0.02) | |
| Corporate Credit Spread | | | -0.05 | | | -0.07 |
| | | | (0.06) | | | (0.06) |
| Δ(Credit-to-GDP Ratio) x Corporate Credit Spread | | | -0.02** | | | -0.02** |
| | | | (0.01) | | | (0.01) |
| Number of Observations | 812 | 257 | 655 | 849 | 266 | 663 |
| Number of Countries | 41 | 21 | 37 | 42 | 21 | 37 |
| $R^2$ | 0.16 | 0.31 | 0.23 | 0.34 | 0.39 | 0.33 |

Source: Authors' estimates.
Note: All regressions are OLS, include country and time fixed effects, and control for real GDP growth and domestic currency appreciation against the US dollar. An increase in the "bank lending standards" variable means stricter bank lending standards. An increase in the financial conditions index means tighter financial conditions. Standard errors are clustered at the country level and shown in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

**Table 3. Riskiness of Credit Allocation and Cumulative GDP Growth**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 1 year | 2-years | 3-years | 1 year | 2-years | 3-years |
| Real GDP Growth | -0.00413 | -0.0947 | -0.201 | 0.0347 | -0.0657 | -0.339*** |
| | (0.0635) | (0.101) | (0.130) | (0.0575) | (0.0912) | (0.121) |
| Δ(Credit-to-GDP Ratio) | -0.102*** | -0.198*** | -0.292*** | -0.106*** | -0.238*** | -0.411*** |
| | (0.0261) | (0.0416) | (0.0536) | (0.0250) | (0.0396) | (0.0524) |
| Financial Conditions Index | -0.524** | -0.810** | -0.889* | -0.353 | -0.641* | -0.978** |
| | (0.238) | (0.379) | (0.488) | (0.232) | (0.368) | (0.487) |
| $ISS^{EDF}$ | -0.0763 | -0.195 | -0.250 | | | |
| | (0.133) | (0.213) | (0.274) | | | |
| $ISS^{Leverage}$ | | | | -0.260* | -0.319 | -0.231 |
| | | | | (0.141) | (0.224) | (0.296) |
| Number of Observations | 586 | 586 | 586 | 658 | 658 | 658 |
| Number of Countries | 40 | 40 | 40 | 42 | 42 | 42 |

Source: Authors' estimates.
Note: All regressions are OLS, include country and time fixed effects. Explanatory variables enter the regression as the lag of their simple three-year moving average. The change in the credit-to-GDP ratio is winsorized at 1 percent. Standard errors are clustered at the country level and shown in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

**Table 4. Riskiness of Credit Allocation and Risks to GDP Growth** (all Deciles)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 |
| Panel A: ISS based on EDF | | | | | | | | | |
| Δ(Credit-to-GDP Ratio) | -0.137** | -0.257*** | -0.261*** | -0.265*** | -0.237*** | -0.274*** | -0.317*** | -0.321*** | -0.339*** |
| | (0.0626) | (0.0293) | (0.0342) | (0.0224) | (0.0191) | (0.0229) | (0.0348) | (0.0225) | (0.0731) |
| Financial Conditions Index | 1.172 | -0.641 | 0.0771 | -0.371 | -0.351 | -0.390 | -1.150** | -1.120** | -1.661** |
| | (0.940) | (0.587) | (0.374) | (0.365) | (0.365) | (0.434) | (0.490) | (0.496) | (0.759) |
| $ISS^{EDF}$ | -0.993*** | -1.321*** | -0.853*** | -0.639*** | -0.565*** | -0.146 | 0.129 | 0.306 | 0.519 |
| | (0.254) | (0.164) | (0.145) | (0.109) | (0.134) | (0.142) | (0.267) | (0.310) | (0.502) |
| Number of Observations | 586 | 586 | 586 | 586 | 586 | 586 | 586 | 586 | 586 |
| Number of Countries | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| Panel B: ISS based on leverage | | | | | | | | | |
| Δ(Credit-to-GDP Ratio) | -0.259*** | -0.264*** | -0.270*** | -0.267*** | -0.244*** | -0.307*** | -0.395*** | -0.462*** | -0.600*** |
| | (0.0462) | (0.0459) | (0.0234) | (0.0164) | (0.0309) | (0.0266) | (0.0304) | (0.0442) | (0.0455) |
| Financial Conditions Index | 2.222*** | 0.209 | -0.0118 | -0.487** | -0.422 | -0.828* | -1.506*** | -1.906*** | -2.519*** |
| | (0.704) | (0.758) | (0.452) | (0.234) | (0.299) | (0.467) | (0.426) | (0.616) | (0.801) |
| $ISS^{Leverage}$ | -0.650** | -0.614*** | -0.743*** | -0.689*** | -0.559*** | -0.163 | 0.169 | 0.531 | 0.832*** |
| | (0.323) | (0.200) | (0.230) | (0.0748) | (0.170) | (0.152) | (0.173) | (0.356) | (0.294) |
| Number of Observations | 658 | 658 | 658 | 658 | 658 | 658 | 658 | 658 | 658 |
| Number of Countries | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |

Source: Authors' estimates.
Note: The estimates shown in columns (1)-(9) are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). The dependent variables are all deciles of the 3-year cumulative GDP growth. Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

**Table 5. Riskiness of Credit Allocation and Downside Risks to Growth** (1st and 2nd Decile of the Cumulative GDP Growth Distribution)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 1 year | | 2 years | | 3 years | |
| | Decile 1 | Decile 2 | Decile 1 | Decile 2 | Decile 1 | Decile 2 |
| Panel A: ISS based on EDF | | | | | | |
| Δ(Credit-to-GDP Ratio) | -0.0158*** | -0.0718*** | -0.129*** | -0.159*** | -0.137** | -0.257*** |
| | (0.00454) | (0.0188) | (0.0320) | (0.0205) | (0.0626) | (0.0293) |
| Financial Conditions Index | 1.517*** | 0.0236 | 0.472 | 0.265 | 1.172 | -0.641 |
| | (0.0309) | (0.399) | (0.915) | (0.485) | (0.940) | (0.587) |
| $ISS^{EDF}$ | -0.0342 | -0.181** | -0.656*** | -0.708*** | -0.993*** | -1.321*** |
| | (0.0487) | (0.0717) | (0.207) | (0.135) | (0.254) | (0.164) |
| Number of Observations | 549 | 549 | 549 | 549 | 549 | 549 |
| Number of Countries | 40 | 40 | 40 | 40 | 40 | 40 |
| Panel B: ISS based on leverage | | | | | | |
| Δ(Credit-to-GDP Ratio) | -0.0441*** | -0.0586*** | -0.188*** | -0.164*** | -0.259*** | -0.264*** |
| | (0.0137) | (0.0156) | (0.0389) | (0.0249) | (0.0462) | (0.0459) |
| Financial Conditions Index | 0.781** | 0.433*** | 1.830 | 0.241 | 2.222*** | 0.209 |
| | (0.349) | (0.143) | (1.187) | (0.525) | (0.704) | (0.758) |
| $ISS^{Leverage}$ | -0.239** | -0.220*** | -0.625** | -0.621*** | -0.650** | -0.614*** |
| | (0.114) | (0.0537) | (0.306) | (0.157) | (0.323) | (0.200) |
| Number of Observations | 658 | 658 | 658 | 658 | 658 | 658 |
| Number of Countries | 42 | 42 | 42 | 42 | 42 | 42 |

Source: Authors' estimates.
Note: The estimates are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

**Table 6. Crisis Prediction Model**

| *Panel A: Riskiness of Credit Allocation Based on EDF* | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ(Credit-to-GDP Ratio) | 0.243** | | 0.0284 | | 0.200* | -0.109 |
| | (0.111) | | (0.164) | | -0.107 | (0.0983) |
| Financial Conditions Index | | -5.290*** | -5.230*** | | | -8.072*** |
| | | (1.432) | (1.491) | | | (2.247) |
| $ISS^{EDF}$ | | | | 1.264** | 1.105** | 3.594*** |
| | | | | (0.497) | (0.534) | (1.042) |
| Number of Observations | 361 | 361 | 361 | 361 | 361 | 361 |
| Number of Countries | 17 | 17 | 17 | 17 | 17 | 17 |
| Number of Crisis Episodes | 17 | 17 | 17 | 17 | 17 | 17 |
| Pseudo $R^2$ | 0.328 | 0.629 | 0.629 | 0.327 | 0.373 | 0.749 |
| *Panel B: Riskiness of Credit Allocation Based on Leverage* | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ(Credit-to-GDP Ratio) | 0.202*** | | 0.120 | | 0.171** | 0.0361 |
| | (0.0699) | | (0.0750) | | (0.0693) | (0.0807) |
| Financial Conditions Index | | -2.468** | -2.234** | | | -3.993*** |
| | | (0.963) | (0.947) | | | (1.055) |
| $ISS^{Leverage}$ | | | | 1.161*** | 1.120** | 2.560*** |
| | | | | (0.362) | -0.491 | (0.746) |
| Number of Observations | 443 | 443 | 443 | 443 | 443 | 443 |
| Number of Countries | 21 | 21 | 21 | 21 | 21 | 21 |
| Number of Crisis Episodes | 21 | 21 | 21 | 21 | 21 | 21 |
| Pseudo $R^2$ | 0.243 | 0.383 | 0.401 | 0.264 | 0.307 | 0.55 |

Source: Authors' estimates.
Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level. The change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

## Table 7a. Downside Risks to Growth - Alternative Credit Series

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Riskiness of Credit Allocation Based on EDF* | | | | | | | | | |
| Real GDP Growth | -0.0546 | 0.0236 | -0.0543 | -0.168* | -0.0274 | 0.0300 | 0.0868 | 0.0757 | -0.161 |
| | (0.144) | (0.0773) | (0.127) | (0.0998) | (0.140) | (0.0883) | (0.115) | (0.0842) | (0.118) |
| Δ(Domestic Bank Private Nonfinancial Credit-to-GDP) (IFS) | -0.257*** | | | | | | | | |
| | (0.0293) | | | | | | | | |
| Δ(Total Private Nonfinancial Credit-to-GDP) (BIS) | | -0.260*** | | | | | | | |
| | | (0.0221) | | | | | | | |
| : to Corporate | | | -0.275*** | | | | | | |
| | | | (0.0472) | | | | | | |
| : to Household | | | | -0.835*** | | | | | |
| | | | | (0.0768) | | | | | |
| : from Domestic Bank | | | | | -0.239*** | | | | |
| | | | | | (0.0398) | | | | |
| Δ(Cross-Border Credit to Non-Banks to GDP) (BIS) | | | | | | -0.197*** | | | |
| | | | | | | (0.0603) | | | |
| Δ(Cross-Border Credit to Banks to GDP) (BIS) | | | | | | | -0.175*** | | |
| | | | | | | | (0.0380) | | |
| Δ(Cross-Border Credit to Banks and Non-Banks to GDP) (BIS) | | | | | | | | -0.145*** | |
| | | | | | | | | (0.0343) | |
| Credit-to-GDP Gap (based on IFS) | | | | | | | | | -0.0778*** |
| | | | | | | | | | (0.00983) |
| Financial Conditions Index | -0.641 | 0.0545 | 1.224* | 0.618 | -0.247 | 0.713 | 0.167 | 0.536 | 0.120 |
| | (0.587) | (0.479) | (0.735) | (0.773) | (0.562) | (0.588) | (0.709) | (0.396) | (0.457) |
| $ISS^{EDF}$ | -1.321*** | -1.426*** | -0.983*** | -0.662*** | -1.349*** | -1.288*** | -1.478*** | -1.435*** | -1.349*** |
| | (0.164) | (0.202) | (0.206) | (0.231) | (0.156) | (0.182) | (0.215) | (0.254) | (0.298) |
| Number of Observations | 586 | 567 | 490 | 490 | 567 | 592 | 592 | 592 | 557 |
| Number of Countries | 40 | 36 | 36 | 36 | 36 | 40 | 40 | 40 | 36 |
| *Panel B: Riskiness of Credit Allocation Based on Leverage* | | | | | | | | | |
| Real GDP Growth | -0.0316 | -0.0898 | -0.388** | -0.389*** | 0.0561 | -0.165 | -0.00524 | 0.0561 | -0.0871* |
| | (0.118) | (0.0858) | (0.161) | (0.150) | (0.0916) | (0.114) | (0.0808) | (0.100) | (0.0469) |
| Δ(Domestic Bank Private Nonfinancial Credit-to-GDP) (IFS) | -0.264*** | | | | | | | | |
| | (0.0459) | | | | | | | | |
| Δ(Total Private Nonfinancial Credit-to-GDP) (BIS) | | -0.223*** | | | | | | | |
| | | (0.0435) | | | | | | | |
| : to Corporates | | | -0.170** | | | | | | |
| | | | (0.0691) | | | | | | |
| : to Households | | | | -1.037*** | | | | | |
| | | | | (0.100) | | | | | |
| : from Domestic Banks | | | | | -0.279*** | | | | |
| | | | | | (0.0736) | | | | |
| Δ(Cross-Border Credit to Non-Banks to GDP) (BIS) | | | | | | -0.383*** | | | |
| | | | | | | (0.0605) | | | |
| Δ(Cross-Border Credit to Banks to GDP) (BIS) | | | | | | | -0.193*** | | |
| | | | | | | | (0.0283) | | |
| Δ(Cross-Border Credit to Banks and Non-Banks to GDP) (BIS) | | | | | | | | -0.149*** | |
| | | | | | | | | (0.0414) | |
| Credit-to-GDP Gap (based on IFS) | | | | | | | | | -0.102*** |
| | | | | | | | | | (0.00602) |
| Financial Conditions Index | 0.209 | 0.725 | 0.657 | -0.438 | 0.116 | 0.607 | 0.0116 | 1.067* | 0.558** |
| | (0.758) | (0.541) | (0.499) | (0.805) | (0.678) | (0.491) | (0.430) | (0.559) | (0.238) |
| $ISS^{Leverage}$ | -0.614*** | -0.321 | -0.351 | 0.314 | -0.585** | -0.912*** | -1.349*** | -1.029*** | -0.101* |
| | (0.200) | (0.222) | (0.305) | (0.237) | (0.295) | (0.206) | (0.0802) | (0.117) | (0.0517) |
| Number of Observations | 658 | 636 | 537 | 537 | 636 | 668 | 668 | 668 | 620 |
| Number of Countries | 42 | 38 | 38 | 38 | 38 | 42 | 42 | 42 | 37 |

Source: Authors' estimates.

Note: The estimates are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

## Table 7b. Crisis prediction - Alternative credit series

| *Panel A: Riskiness of Credit Allocation Based on EDF* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Δ(Domestic Bank Credit-to-GDP) (IFS) | -0.109 | | | | | | | | |
| | (0.0983) | | | | | | | | |
| Δ(Credit-to-GDP) to Non-Financial Private Sector (BIS) | | 0.126 | | | | | | | |
| | | (0.167) | | | | | | | |
| : to Corporates | | | 0.151 | | | | | | |
| | | | (0.138) | | | | | | |
| : to Households | | | | -0.0641 | | | | | |
| | | | | (0.391) | | | | | |
| : from Domestic Banks | | | | | 0.0512 | | | | |
| | | | | | (0.136) | | | | |
| Δ(Cross-Border Credit to Non-Banks to GDP) (BIS) | | | | | | 0.00891 | | | |
| | | | | | | (0.315) | | | |
| Δ(Cross-Border Credit to Banks to GDP) (BIS) | | | | | | | -0.00407 | | |
| | | | | | | | (0.120) | | |
| Δ(Cross-Border Credit to Banks and Non-Banks to GDP) (BIS) | | | | | | | | -0.00160 | |
| | | | | | | | | (0.0818) | |
| Credit-to-GDP Gap (BIS) | | | | | | | | | 0.0189 |
| | | | | | | | | | (0.0757) |
| Financial Conditions Index | -8.072*** | -7.780*** | -9.223*** | -9.078*** | -7.601*** | -7.702*** | -7.715*** | -7.699*** | -7.552*** |
| | (2.247) | (1.902) | (2.340) | (2.237) | (1.977) | (2.033) | (2.338) | (2.126) | (2.142) |
| $ISS^{EDF}$ | 3.594*** | 3.519*** | 4.439*** | 4.227*** | 3.405*** | 3.358*** | 3.359*** | 3.355*** | 3.401*** |
| | (1.042) | (0.882) | (1.242) | (1.140) | (0.887) | (0.923) | (0.983) | (0.946) | (0.872) |
| Number of Observations | 361 | 361 | 311 | 311 | 361 | 361 | 361 | 361 | 362 |
| Number of Countries | 17 | 17 | 15 | 15 | 17 | 17 | 17 | 17 | 17 |
| Number of Crisis Episodes | 17 | 17 | 15 | 15 | 17 | 17 | 17 | 17 | 17 |
| Pseudo $R^2$ | 0.749 | 0.751 | 0.770 | 0.762 | 0.745 | 0.744 | 0.744 | 0.744 | 0.744 |
| *Panel B: Riskiness of Credit Allocation Based on Leverage* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Δ(Domestic Bank Credit-to-GDP) (IFS) | 0.0361 | | | | | | | | |
| | (0.0807) | | | | | | | | |
| Δ(Credit-to-GDP) to Non-Financial Private Sector (BIS) | | 0.0486 | | | | | | | |
| | | (0.0832) | | | | | | | |
| : to Corporates | | | 0.0199 | | | | | | |
| | | | (0.138) | | | | | | |
| : to Households | | | | 0.108 | | | | | |
| | | | | (0.331) | | | | | |
| : from Domestic Banks | | | | | 0.0794 | | | | |
| | | | | | (0.103) | | | | |
| Δ(Cross-Border Credit to Non-Banks to GDP) (BIS) | | | | | | 0.00790 | | | |
| | | | | | | (0.170) | | | |
| Δ(Cross-Border Credit to Banks to GDP) (BIS) | | | | | | | 0.196* | | |
| | | | | | | | (0.101) | | |
| Δ(Cross-Border Credit to Banks and Non-Banks to GDP) (BIS) | | | | | | | | 0.102** | |
| | | | | | | | | (0.0483) | |
| Credit-to-GDP Gap (BIS) | | | | | | | | | 0.0367 |
| | | | | | | | | | (0.0425) |
| Financial Conditions Index | -3.993*** | -3.980*** | -4.408*** | -4.316*** | -3.910*** | -4.110*** | -3.652*** | -3.748*** | -4.047*** |
| | (1.055) | (1.036) | (1.220) | (1.226) | (1.034) | (1.051) | (0.928) | (0.974) | (1.106) |
| $ISS^{Leverage}$ | 2.560*** | 2.497*** | 2.548*** | 2.572*** | 2.506*** | 2.601*** | 2.417*** | 2.373*** | 2.495*** |
| | (0.746) | (0.775) | (0.849) | (0.758) | (0.746) | (0.722) | (0.699) | (0.768) | (0.720) |
| Number of Observations | 443 | 443 | 375 | 375 | 443 | 443 | 443 | 443 | 443 |
| Number of Countries | 21 | 21 | 19 | 19 | 21 | 21 | 21 | 21 | 21 |
| Number of Crisis Episodes | 21 | 21 | 19 | 19 | 21 | 21 | 21 | 21 | 21 |
| Pseudo $R^2$ | 0.550 | 0.551 | 0.563 | 0.565 | 0.554 | 0.549 | 0.578 | 0.564 | 0.556 |

Source: Authors' estimates.

Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

**Table 8a. Downside Risks to Growth - Alternative Firm Vulnerability Indicators**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 1 year | | 2 years | | 3 years | |
| | Decile 1 | Decile 2 | Decile 1 | Decile 2 | Decile 1 | Decile 2 |
| Panel A: ISS based on ICR | | | | | | |
| Real GDP Growth | 0.0995* | 0.102*** | -0.0329 | 0.0374 | -0.104 | -0.0950 |
| | (0.0574) | (0.0359) | (0.0698) | (0.0453) | (0.0658) | (0.0848) |
| Δ(Credit-to-GDP Ratio) | -0.0568*** | -0.0704*** | -0.114*** | -0.168*** | -0.199*** | -0.211*** |
| | (0.0186) | (0.0143) | (0.0315) | (0.0248) | (0.0593) | (0.0204) |
| Financial Conditions Index | 0.526* | 0.115 | 1.764*** | -0.328 | 1.846*** | 0.0361 |
| | (0.277) | (0.168) | (0.198) | (0.423) | (0.360) | (0.541) |
| $ISS^{ICR}$ | -0.160 | -0.186** | -1.004*** | -0.691*** | -1.500*** | -1.398*** |
| | (0.219) | (0.0810) | (0.377) | (0.177) | (0.293) | (0.238) |
| Number of Observations | 651 | 651 | 651 | 651 | 651 | 651 |
| Number of Countries | 42 | 42 | 42 | 42 | 42 | 42 |
| Panel B: ISS based on debt/EBITDA | | | | | | |
| Real GDP Growth | 0.106* | 0.124*** | 0.0322 | 0.0852* | -0.123 | -0.0841 |
| | (0.0554) | (0.0397) | (0.0573) | (0.0436) | (0.133) | (0.0992) |
| Δ(Credit-to-GDP Ratio) | -0.0601*** | -0.0748*** | -0.140*** | -0.184*** | -0.307*** | -0.222*** |
| | (0.0165) | (0.0159) | (0.0303) | (0.0223) | (0.0417) | (0.0271) |
| Financial Conditions Index | 0.614** | 0.107 | 1.325* | -0.0525 | 1.849*** | -0.0268 |
| | (0.241) | (0.196) | (0.718) | (0.491) | (0.177) | (0.621) |
| $ISS^{Debt/EBITDA}$ | -0.0987 | -0.0866 | -0.296 | -0.172 | -0.322 | -0.609*** |
| | (0.166) | (0.0839) | (0.199) | (0.125) | (0.235) | (0.172) |
| Number of Observations | 648 | 648 | 648 | 648 | 648 | 648 |
| Number of Countries | 42 | 42 | 42 | 42 | 42 | 42 |

Source: Authors' estimates.
Note: The estimates are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

**Table 8b. Crisis prediction - Alternative Firm Vulnerability Indicators**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Δ(Credit-to-GDP Ratio) | 0.202*** | | 0.120 | | 0.185** | 0.0593 | | 0.168** | 0.0584 |
| | (0.0699) | | (0.0750) | | (0.0839) | (0.109) | | (0.0815) | (0.108) |
| Financial Conditions Index | | -2.468** | -2.234** | | | -4.581*** | | | -3.616*** |
| | | (0.963) | (0.947) | | | (1.615) | | | (0.867) |
| $ISS^{Debt/EBITDA}$ | | | | 1.393*** | 1.401*** | 2.749*** | | | |
| | | | | (0.404) | (0.494) | (0.672) | | | |
| $ISS^{ICR}$ | | | | | | | 1.557** | 1.488* | 3.082*** |
| | | | | | | | (0.624) | (0.781) | (1.132) |
| Number of Observations | 443 | 443 | 443 | 431 | 431 | 431 | 432 | 432 | 432 |
| Number of Countries | 21 | 21 | 21 | 20 | 20 | 20 | 20 | 20 | 20 |
| Number of Crisis Episodes | 21 | 21 | 21 | 20 | 20 | 20 | 20 | 20 | 20 |
| Pseudo $R^2$ | 0.243 | 0.383 | 0.353 | 0.298 | 0.342 | 0.611 | 0.262 | 0.304 | 0.548 |

Source: Authors' estimates.
Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

## Table 9a. Downside Risks to Growth - Alternative constructions of the Riskiness of Credit Allocation

| Alternative ISS constructions | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Based on EDF | | | Based on Leverage | | |
| | Beta | Std | Obs. | Beta | Std | Obs. |
| (0) Baseline | -1.321*** | (0.164) | 586 | -0.614*** | (0.200) | 658 |
| Alternative vulnerability scale | | | | | | |
| (1) Simple average of raw vulnerability | -0.120*** | (0.0229) | 586 | -7.586*** | (2.397) | 658 |
| Alternative weighting | | | | | | |
| (2) Debt-weighted deciles | -0.856*** | -0.239 | 586 | 0.0246 | (0.334) | 658 |
| Alternative sorting | | | | | | |
| (3) By net debt issuance in USD | -0.962*** | (0.193) | 586 | -0.948*** | (0.193) | 658 |
| (4) By vulnerability | -1.339*** | (0.132) | 586 | -0.953*** | (0.253) | 658 |
| Alternative vulnerability scale and sorting | | | | | | |
| (5) = (1) & (3) | -0.0563*** | (0.0241) | 586 | -9.957* | (2.948) | 658 |

Source: Authors' estimates.
Note: The table shows estimated coefficients of the riskiness of credit allocation in the downside-risks-to-growth model, as in Table 5, column (6). Row (0) reproduces the results obtained with the baseline ISS. The alternative indictors are constructed as follows: in row (1), the raw vulnerability measure is used (instead of its decile); in row (2), the vulnerability measure transformed into a decile is weighted by debt; in row (3), firms are sorted by the absolute amount of their debt issuance (instead of their debt issuance normalized by lagged assets); in row (4), firms are sorted by vulnerability level (instead of net debt issuance) and we take the difference in average net debt issuance to assets (transformed into deciles) across top vulnerability and bottom vulnerability firms; in row (5), we combine perturbations (1) and (3). All explanatory variables enter the regression as the lag of their simple three-year moving average. The change in the credit-to-GDP ratio, the FCI, and real GDP growth are included in all regressions. *** *p*<0.01; ** *p*<0.05; * *p*<0.1.

## Table 9b. Crisis prediction - Alternative constructions of the Riskiness of Credit Allocation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Alternative ISS constructions | Based on Expected Default Frequency | | | | Based on Leverage | | | |
| | Beta | Std | Pseudo $R^2$ | Obs. | Beta | Std | Pseudo $R^2$ | Obs. |
| (0) Baseline | 3.594*** | (1.042) | 0.749 | 361 | 2.560*** | (0.746) | 0.55 | 443 |
| Alternative vulnerability scale | | | | | | | | |
| (1) Simple average of raw vulnerability | 0.381*** | (0.111) | 0.7 | 361 | 40.81*** | (14.79) | 0.543 | 443 |
| Alternative weighting | | | | | | | | |
| (2) Debt-weighted deciles | 1.761*** | (0.624) | 0.701 | 361 | 1.913** | (0.865) | 0.485 | 443 |
| Alternative sorting | | | | | | | | |
| (3) By net debt issuance in USD | 3.159*** | (1.075) | 0.704 | 361 | 1.786*** | (0.572) | 0.466 | 443 |
| (4) By vulnerability | 3.007** | (1.305) | 0.739 | 361 | 1.537** | (0.729) | 0.498 | 443 |
| Alternative vulnerability scale and sorting | | | | | | | | |
| (5) = (1) & (3) | 0.393*** | (0.122) | 0.685 | 361 | 29.63*** | (7.599) | 0.475 | 443 |

Source: Authors' estimates.
Note: The table shows estimated coefficients of the riskiness of credit allocation in the crisis prediction model, as in columns (7) and (10) of Table 3. Row (0) reproduces the results obtained with the baseline ISS. The alternative indictors are constructed as follows: in row (1), the raw vulnerability measure is used (instead of its decile); in row (2), the vulnerability measure transformed into a decile is weighted by debt; in row (3), firms are sorted by the absolute amount of their debt issuance (instead of their debt issuance normalized by lagged assets); in row (4), firms are sorted by vulnerability level (instead of net debt issuance) and we take the difference in average net debt issuance to assets (transformed into deciles) across top vulnerability and bottom vulnerability firms; in row (5), we combine perturbations (1) and (3). All explanatory variables enter the regression as the lag of their simple three-year moving average. Country fixed effects, the change in the credit-to-GDP ratio, the FCI, the change in current-account-to-GDP ratio, and real GDP growth are included in all regressions. *** *p*<0.01; ** *p*<0.05; * *p*<0.1.

## Table 10. Riskiness of Credit Allocation and Change in the Share of Vulnerable Assets

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent Variable: ΔShare of Assets in Firms with High Vulnerability | | | | | |
| | Leverage>p75 | ICR<p25 | Debt-to-EBITDA Ratio>P75 | Leverage>p75 | ICR<p25 | Debt-to-EBITDA Ratio>P75 |
| ΔCredit-to-GDP | 0.18*** | 0.32*** | 0.36*** | 0.10* | 0.21** | 0.24*** |
| | (0.05) | (0.09) | (0.09) | (0.06) | (0.09) | (0.08) |
| FCI | 0.85*** | 1.49*** | 1.46*** | 0.89*** | 1.42*** | 1.45*** |
| | (0.23) | (0.23) | (0.26) | (0.21) | (0.21) | (0.26) |
| $ISS^{EDF}$ | 1.11*** | 1.08*** | 0.65** | | | |
| | (0.30) | (0.31) | (0.32) | | | |
| $ISS^{Leverage}$ | | | | 2.50*** | 2.81*** | 2.24*** |
| | | | | (0.31) | (0.51) | (0.46) |
| Number of Observations | 812 | 812 | 805 | 842 | 842 | 833 |
| Number of Countries | 41 | 41 | 41 | 42 | 42 | 42 |
| $R^2$ | 0.04 | 0.07 | 0.08 | 0.11 | 0.14 | 0.12 |

Source: Authors' estimates

Note: All regressions are OLS and include country fixed effects. Standard errors are clustered at the country level and shown in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

## Table 11. Riskiness of Credit allocation and Reversal in Financial Conditions

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Dependent Variable: | | | | | | | |
| | ΔFCI | | | | Δspread | | | |
| FCI | -0.68*** | -1.45*** | -0.67*** | -1.41*** | | | | |
| | (0.03) | (0.08) | (0.03) | (0.08) | | | | |
| Corporate Credit Spread | | | | | -0.35*** | -0.41*** | -0.36*** | -0.34*** |
| | | | | | (0.04) | (0.08) | (0.04) | (0.08) |
| $ISS^{EDF}$ | 0.11** | 0.27*** | | | 0.12** | 0.12** | | |
| | (0.05) | (0.09) | | | (0.04) | (0.06) | | |
| $ISS^{Leverage}$ | | | 0.08** | 0.25*** | | | 0.05* | 0.13** |
| | | | (0.04) | (0.08) | | | (0.03) | (0.05) |
| Sample | Full | l.FCI_mv3<0 | Full | l.FCI_mv3<0 | Full | l.spread_mv3<0 | Full | l.spread_mv3<0 |
| Number of Observations | 707 | 348 | 780 | 377 | 552 | 328 | 580 | 345 |
| Number of Countries | 40 | 40 | 42 | 41 | 37 | 37 | 37 | 37 |
| $R^2$ | 0.28 | 0.30 | 0.29 | 0.31 | 0.15 | 0.06 | 0.14 | 0.08 |

Source: Authors' estimates.

Note: All regressions are OLS and include country fixed effects. The dependent variable is the change in FCI for columns (1)–(4) and the change in the corporate credit spread in columns (5)-(8). Explanatory variables enter as the lag of their simple three-year moving average. In columns (2) and (4), the sample is restricted to observations for which the lag of the FCI's simple three-year moving average is negative. In columns (6) and (8), the sample is restricted to observations for which the lag of the spread's simple three-year moving average is negative. Standard errors, clustered at the country level, are shown in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

**Table 12. Riskiness of Credit allocation, GDP Growth Forecast, and Forecast Error**

| | (1)<br>Actual | (2)<br>Forecast | (3)<br>Error | (4)<br>Actual | (5)<br>Forecast | (6)<br>Error |
|---|---|---|---|---|---|---|
| Panel A: ISS based on EDF | | | | | | |
| Δ(Credit-to-GDP Ratio) | -0.29*** | -0.01 | 0.28*** | -0.41*** | 0.00 | 0.41*** |
| | (0.05) | (0.02) | (0.06) | (0.05) | (0.02) | (0.06) |
| Financial Conditions Index | -0.89* | -0.13 | 0.76 | -0.98** | -0.01 | 0.97* |
| | (0.49) | (0.21) | (0.51) | (0.49) | (0.21) | (0.51) |
| $ISS^{EDF}$ | -0.25 | 0.28** | 0.53* | | | |
| | (0.27) | (0.12) | (0.29) | | | |
| $ISS^{Leverage}$ | | | | -0.23 | 0.31** | 0.55* |
| | | | | (0.3) | (0.13) | (0.31) |
| Number of Observations | 586 | 586 | 586 | 658 | 658 | 658 |
| Number of Countries | 40 | 40 | 40 | 42 | 42 | 42 |

Source: Authors' estimates.
Note: The estimates are obtained through OLS with time and country fixed effects. Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

## Appendix A. Data Sources and Definitions

### Firm level data

Sample - The paper uses annual firm-level data from the Worldscope database, which covers the universe of listed firms in most countries around the world. Starting from the full Worldscope universe of firms, the sample is first cleaned by dropping financial sector firms (except those in the real estate sector). Second, observations are dropped when market capitalization, total assets, total debt, total liability, or interest expenses are strictly negative; or when the operating profit margin or the ratio of short-term debt to total debt is larger than 100 percent. Third, observations are kept only if full information on net debt issuance; leverage; earnings before interest, taxes, depreciation, and amortization (EBITDA); and market capitalization is available. Then, only country-year pairs with no fewer than 40 firms and available information on aggregate credit to the private sector are kept.[25] At the end of this cleaning procedure, about 500,000 nonfinancial firm-year observations from 55 countries during 1990 to 2016 are left in the sample. Country coverage is summarized in Annex Table A1.

Firm vulnerability indicators - The leverage ratio is defined as the ratio of total debt to total assets. The expected default frequency (EDF) is computed using the Black-Scholes-Merton model. Details of the construction, including data series used for the risk-free rate, are provided in the Online Appendix. The interest coverage ratio (ICR) is defined as the ratio of interest expenses to EBITDA. The debt/EBITDA ratio is defined as the ratio of total debt to EBITDA.

The sign of the ISS for the ICR is adjusted so that it rises when the vulnerability of top issuers is increasing. For debt overhang, the deciles of EBITDA to debt (instead of debt to EBITDA) are used to avoid classifying firms with negative earnings as low-vulnerability firms.

### Macrofinancial data

Macrofinancial data sources, definitions, and transformations used in the paper are summarized in Appendix Table A2. Details of the construction of the financial conditions index are provided in the Online Appendix B.

[25] For the construction of the interest coverage ratio–based indicator, a minimum of 40 observations for interest expenses is also required. An exception is made for one borderline case (Ireland), for which some years only have 38 or 39 observations. For the construction of the ISS indicator based on debt/EBITDA, a minimum of 40 observations for non-zero debt is also required. For the construction of the ISS indicator based on expected default frequency, a minimum of 40 observations for expected default frequency is also required.

**Appendix Table A.1. Country Coverage**

| | ISS series from | Banking crisis start year | | ISS series from | Banking crisis start year |
|---|---|---|---|---|---|
| **Advanced Economies** | | | **Emerging Market Economies** | | |
| Australia* | 1991 | | Argentina* | 2000 | 2001 |
| Austria* | 1991 | 2008 | Brazil* | 1992 | 1994 |
| Belgium* | 1991 | 2008 | Bulgaria* | 2006 | |
| Canada* | 1991 | 2000 | Chile* | 1995 | |
| Czech Republic* | 1997 | | China* | 2000 | |
| Denmark* | 1991 | 2008 | Croatia | 2006 | |
| Finland* | 1991 | | Egypt | 2006 | |
| France* | 1991 | 2008 | India* | 1993 | |
| Germany* | 1991 | 2000 | Indonesia* | 1992 | 1997 |
| Greece* | 1994 | 2008 | Jordan | 2006 | |
| Hong Kong SAR | 1991 | | Kuwait | 2006 | |
| Ireland* | 1999 | 2008 | Malaysia* | 1991 | 1997 |
| Israel* | 2000 | | Mexico* | 1995 | |
| Italy* | 1991 | 2008 | Morocco | 2009 | |
| Japan* | 1991 | 1997 | Oman | 2006 | |
| Korea* | 1993 | 1997 | Pakistan | 1995 | |
| Netherlands* | 1991 | 2008 | Peru* | 2001 | |
| New Zealand* | 1999 | | Philippines* | 1996 | |
| Norway* | 1991 | | Poland* | 2000 | |
| Portugal* | 1996 | 2008 | Romania | 2006 | |
| Singapore | 1991 | | Russia* | 2005 | 2008 |
| Spain* | 1991 | 2008 | Saudi Arabia | 2006 | |
| Sweden* | 1991 | 2008 | Serbia | 2010 | |
| Switzerland* | 1991 | 2008 | South Africa* | 1991 | |
| United Kingdom* | 1991 | 2007 | Sri Lanka | 2006 | |
| United States* | 1991 | 2007 | Thailand* | 1993 | 1997 |
| | | | Turkey* | 1997 | 2000 |
| | | | Ukraine | 2008 | 2014 |
| | | | Vietnam* | 2007 | |

# Appendix Table A.2. Country-Level Data Sources

| Variable | Description | Source |
| --- | --- | --- |
| Real GDP growth | Annual percentage change in the gross domestic product, constant prices in national currency. | IMF, World Economic Outlook database |
| Real GDP growth forecast | Annual percentage change in the gross domestic product forecast, constant prices in national currency. | IMF, World Economic Outlook database |
| Nominal GDP | Gross domestic product, current prices in national currency. | IMF, World Economic Outlook database |
| Inflation | Annual percentage change in the consumer price index. | Haver Analytics; IMF, International Finance Statistics |
| Current account | Current account balance, in US dollars. | IMF, World Economic Outlook database |
| Exchange rate | National currency per US dollar. | IMF, International Financial Statistics and World Economic Outlook databases |
| Real Effective Exchange Rate | Real effective exchange rate, based on the consumer price index. | IMF, International Financial Statistics |
| International Reserves | Total reserves excluding gold in US dollars | IMF, International Financial Statistics |
| Lending Standards | Cumulative net percentage balance (or diffusion index) of the weighted percentage of surveyed financial institutions reporting tightened credit standards minus the weighted percentage reporting eased credit standards. The variable is transformed into a z-score at the country level. An increase of this index implies a net tightening. | Haver Analytics; IMF staff estimates |
| Financial Conditions Index | For methodology and variables included in the FCI, see the Online Appendix. Positive values of the FCI indicate tighter-than-average financial conditions. | Authors' estimates |
| Long-term Interest Rate | 10-year government bond yield | Bloomberg Finance L.P |
| Corporate Spreads | 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. The variable is transformed into a z-score at the country level. | Bloomberg Finance L.P.; Thomson Reuters Datastream |
| Credit to Private Sector (baseline) | Credit provided to the private sector by domestic money banks. | IMF, International Financial Statistics |
| Credit to Private Sector | Total credit to the private non-financial sector in billions of domestic currency | BIS CRE Table F2.3 |
| Credit to Corporate Sector | Total credit to non-financial corporations in billions of domestic currency | BIS CRE Table F4.3 |
| Credit to Household Sector | Total credit to households in billions of domestic currency | BIS CRE Table F3.3 |
| Credit to Private Sector from Domestic Banks | Bank credit to the private non-financial sector in billions of domestic currency | BIS CRE Table F2.6 |
| Cross-Border Credit to Private Sector | Cross-border claims of BIS-reporting banks on banks and non-banks in billions of US dollars | BIS LBS A6.1-F |
| Cross-Border Credit to Banks | Cross-border claims of BIS-reporting banks on banks in billions of US dollars | BIS LBS A6.1-F |
| Cross-Border Credit to Non-Banks | Cross-border claims of BIS-reporting banks on non-banks in billions of US dollars | BIS LBS A6.1-F |
| Systemic Banking Crisis | Dummy for systemic banking crisis start year | Laeven and Valencia (2018) |