CHAPTER 2

THE RISKINESS OF CREDIT ALLOCATION: A SOURCE OF FINANCIAL VULNERABILITY?

Summary

The prolonged period of loose financial conditions in recent years has raised concerns that financial intermediaries and investors in search of yield may have extended too much credit to risky borrowers, potentially jeopardizing financial stability down the road. These concerns are related to recent evidence for selected countries that periods of low interest rates and easy financial conditions may lead to a decline in lending standards and increased risk taking.

Against this backdrop, this chapter takes a comprehensive look at the evolution of the riskiness of corporate credit allocation—that is, the extent to which riskier firms receive credit relative to less risky ones, its relationship to the strength of credit expansions, and its relevance to financial stability analysis for a large number of advanced and emerging market economies since 1991. The chapter focuses on the allocation of credit across firms rather than the aggregate volume of credit or credit growth.

The chapter finds that the riskiness of credit allocation rises during periods of fast credit expansion, especially when loose lending standards or easy financial conditions occur concurrently. Globally, the riskiness of credit allocation increased in the years preceding the global financial crisis and peaked shortly before its onset. It declined sharply after the crisis and rebounded to its historical average in 2016, the latest available year for globally comparable data. As financial conditions loosened in 2017, the riskiness of credit allocation might have risen further.

An increase in the riskiness of credit allocation signals heightened downside risks to GDP growth and a higher probability of banking crises and banking sector stress, over and above the previously documented signals provided by credit growth. Thus, a riskier allocation of corporate credit is an independent source of financial vulnerability.

The results highlight the importance of monitoring the riskiness of credit allocation as an integral part of macro-financial surveillance. The new measures constructed in this chapter are simple to compute, rely mostly on firm-level financial statement data that are available in many countries, and can be readily replicated for use in macro-financial surveillance. For this purpose, policymakers would benefit from collecting these data in a timely manner.

The chapter shows that various policy and institutional settings may help policymakers mitigate the increase in the riskiness of credit allocation that takes place during relatively fast credit expansions. A tightening of the macroprudential policy stance, greater independence of the supervisory authority from banks, a smaller government footprint in the corporate sector, and greater minority shareholder protection are all related to a smaller increase in the riskiness of corporate credit allocation during these episodes.

Introduction

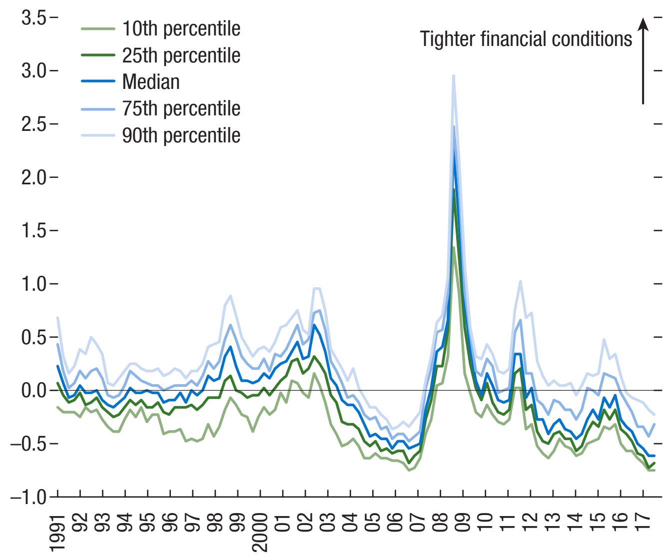
After years of accommodative monetary policy, financial conditions remain loose in most advanced and emerging market economies. Although withdrawal of monetary policy stimulus has begun in several advanced economies and is expected to keep proceeding at a gradual pace in the United States, and despite a recent rebound in financial market volatility, financial conditions have remained loose, and spreads (including corporate spreads) have remained compressed by historical standards in both advanced and emerging market economies (see Figure 2.1 and Chapter 1). Meanwhile, corporate credit-to-GDP ratios remain at or near their historical highs in both advanced economies and emerging markets.[1]

This environment has raised concerns among policymakers and market analysts that nonfinancial corporate credit might have been excessively allocated to risky firms, especially in advanced economies, jeopardizing financial stability down the road. As described in Chapter 1, persistently easy financial conditions may lead to a continued search for yield with too much money chasing too few yielding assets, pushing investors beyond their traditional risk tolerance into riskier investments. Indeed, the share of bond issuance by nonfinancial corporations with low ratings (high-yield and BBB-rated bonds) has rebounded from its crisis trough in the United States and is at or near an all-time high in the euro area and the United Kingdom (Figure 2.2). At the same time, the October 2017 *Global Financial Stability Report* (GFSR) highlighted that some indicators of nonfinancial corporate vulnerability had picked up in several major economies. Although greater risk taking by financial intermediaries could be part of a healthy economic recovery, it may breed vulnerabilities that could harm future growth if excessive.

Country-level studies have documented that the composition of corporate credit flows changes with financial conditions and that the riskiness of corporate credit allocation is procyclical. The riskiness of corporate credit allocation is the extent to which riskier firms receive credit relative to less risky firms. Empirical studies dating to the mid-1990s for the United States provide evidence that the riskiness of corporate credit allocation increases during economic expansions and declines during recessions (for example, Lang and Nakamura 1995; Bernanke, Gertler, and Gilchrist 1996).[2] More recently, Greenwood and Hanson (2013) offer further evidence of such behavior in the United States during the past few decades: the riskiness of corporate credit allocation rises when credit growth is stronger, the short-term Treasury bill yield is lower, the term spread is lower, or high-yield bond returns are higher. Corroborating evidence comes from Spain, where riskier firms had nearly the same access to the bank loan market as less risky firms in the years preceding the global financial crisis, but significantly less access during the crisis and early recovery period (Banco de España 2017). In the euro area, riskier firms increased their borrowing more than less risky firms following the rally in euro area sovereign bonds triggered by the European Central Bank's

Figure 2.1. Financial Conditions Have Been Loose in Recent Years

(Financial conditions index; various percentiles of the cross-country distribution)



Source: IMF staff estimates.
Note: A higher level of the financial conditions index (FCI) means financial conditions are tighter. The sample comprises 41 advanced and emerging market economies. For methodology and variables included in the FCI, refer to Annex 3.2 of the October 2017 *Global Financial Stability Report.*

Prepared by a staff team led by Jérôme Vandenbussche and composed of Luis Brandão-Marques, Qianying Chen, Oksana Khadarina, and Peichu Xie under the general guidance of Claudio Raddatz and Dong He. The chapter benefited from contributions by Divya Kirti and Jiaqi Li. Claudia Cohen and Breanne Rajkumar provided editorial assistance.

[1]See IMF (2016) and the October 2015 GFSR for recent analyses of the evolution of corporate debt across countries.

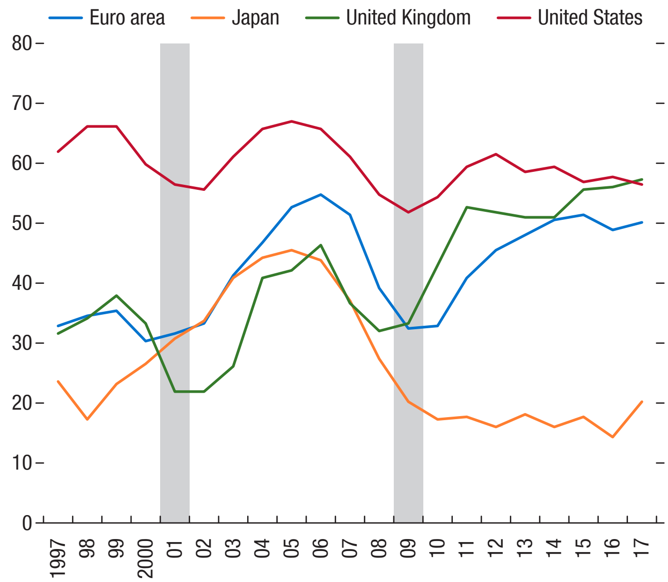
[2]A decline in the riskiness of credit allocation during recessions has sometimes been referred to as a "flight to quality."

announcement in 2012 that it stood ready to conduct Outright Monetary Transactions (Acharya and others 2016). Analyses of granular data from Spain and the United States also reveal a positive association between low short-term interest rates and the probability of extending loans to risky borrowers (Jiménez and others 2014; Dell'Ariccia, Laeven, and Suarez 2017).

Against this backdrop, this chapter takes a comprehensive look at the evolution of the riskiness of corporate credit allocation, its relationship to the size of credit expansions, and its relevance to financial stability analysis.

- No cross-country measures are readily available that capture the riskiness of total credit flows across firms. To fill this gap, this chapter constructs several measures that map the flow of credit across firms to the distribution of various firm-level vulnerability indicators for 55 economies since 1991.[3] Existing methodologies for assessing firm-level vulnerability or default risk may be more or less suitable to different market and data environments. For this reason, the chapter discusses four options for measuring the riskiness of corporate credit allocation—henceforth, the "riskiness of credit allocation." In constructing these measures, this chapter provides the most comprehensive cross-country analysis of the riskiness of credit allocation to date.
- Financial stress and growth-at-risk models in the empirical literature have focused on changes in aggregate credit volumes as the key vulnerability measure.[4] Although it may seem intuitive that a measure capturing the extent to which credit is flowing to riskier firms can provide additional information on future macro-financial outcomes, this proposition has remained, at best, a matter of conjecture in the financial stability literature.[5] Furthermore, standard indicators of aggregate corporate vulnerability, which are discussed in most financial stability reports around the world, do not take firm-level credit flows into consideration.[6]

Figure 2.2. Low-Rated Nonfinancial Corporate Bond Issuance Has Been High in Some Advanced Economies
(Percent of total nonfinancial corporate bond issuance)



Sources: Dealogic; and IMF staff estimates.
Note: "Low-rated" refers to high-yield and BBB-rated bonds; the simple three-year moving average is shown. Shaded areas indicate periods during which global real GDP growth was less than 2.5 percent.

Following a conceptual discussion of the relationship between the riskiness of credit allocation and credit growth, this chapter addresses the following questions:

- How has the riskiness of credit allocation evolved in recent years across a broad spectrum of advanced economies and emerging markets?

[3]Some studies have relied on indirect measures such as bond issuance data by level of credit rating (for example, Kirti 2018). Others have focused on the share of credit flowing to distressed ("zombie") firms. The former measures ignore a significant source of credit (loans) and are not well suited to most emerging markets and advanced economies of relatively small size, where domestic bond market development is low. The latter are partial because they focus only on two categories of firms (distressed and nondistressed).

[4]See Schularick and Taylor (2012), Gourinchas and Obstfeld (2012), Dell'Ariccia and others (2016), Baron and Xiong (2017), and Chapters 2 and 3 of the October 2017 GFSR. Gourinchas and Obstfeld (2012) also emphasize the importance of external imbalances, especially in emerging markets. Jordà, Schularick, and Taylor (2016b) find that in advanced economies financial crises are not more likely when public debt is high. However, they show that high levels of public debt tend to exacerbate the effects of private sector deleveraging after financial crises, as does IMF (2016). Recent papers also suggest that credit spreads—the extra yield paid by bonds issued by firms with low credit ratings relative to firms with the best credit ratings—are particularly low before a financial crisis (Krishnamurthy and Muir 2017). López-Salido, Stein, and Zakrajšek (2017) provide evidence that low credit spreads by themselves forecast poor future economic performance in the United States.

[5]In the conclusion to their paper, Jiménez and others (2014) conjecture that the compositional change in the supply of credit with respect to risk is more important for financial stability than the volume of credit. Kirti (2018) shows that an increase in the share of high-yield bond issuance during a credit boom predicts lower future growth (see also Box 2.4).

[6]For a conceptual framework of financial stability monitoring, see Adrian, Covitz, and Liang (2015).

- How does the riskiness of credit allocation relate to measures of financial conditions over time? Does it generally rise during periods of high credit growth? Is it more likely to increase when high credit growth is associated with strong risk appetite?
- To what extent does the riskiness of credit allocation help predict financial sector stress and downside risks to GDP growth? How far in advance can it predict these occurrences? Do the predictive properties of the riskiness of credit allocation reinforce those of credit growth documented in the existing literature?
- How is the dynamic of the riskiness of credit allocation affected by the regulatory, supervisory, and legal environments? What is the link between the cyclicality of the riskiness of credit allocation and common indicators of banking sector soundness?

The main findings of the chapter follow:

- Taking the riskiness of credit allocation into account helps better predict full-blown banking crises, financial sector stress, and downside risks to growth at horizons up to three years. Thus, the riskiness of credit allocation is an indicator of financial vulnerability.
- A period of high credit growth is more likely to be followed by a severe downturn over the medium term if it is accompanied by an increase in the riskiness of credit allocation. By contrast, when credit is stagnant or falling, the riskiness of credit allocation has a negligible effect on downside risks to GDP growth.
- The riskiness of credit allocation at the global level has followed a cyclical pattern over the past 25 years, has rebounded since its post-global-financial-crisis trough, and was slightly below its historical average at the end of 2016 (the latest data point).
- At the country level, the riskiness of credit allocation is more strongly associated with credit growth when lending standards are easier, when domestic financial conditions are looser, when credit spreads are lower, and when global risk appetite is higher.
- A period of credit expansion is less likely to be associated with a riskier credit allocation when macroprudential policy has been tightened, when the banking supervisor is more independent, when the government has a smaller footprint in the nonfinancial corporate sector, and when minority shareholder protection is greater.

The remainder of the chapter is organized as follows: The chapter first lays out a stylized conceptual framework for macro-financial shocks and the riskiness of credit allocation. It then describes the construction of the new measures, their evolution at the global level and in selected economies, their cyclical properties, and their relationship to various indicators of financial conditions. Next, the chapter turns to the empirical analysis of the relationship between the new indicators and future financial instability as well as downside risks to GDP growth. The last core section further explores determinants of the riskiness of credit allocation and its cyclicality, including macroprudential policies and aspects of the supervisory, legal, and institutional frameworks. The last section concludes and presents policy implications.

The Riskiness of Credit Allocation: Conceptual Framework

The theoretical literature has identified various mechanisms through which the riskiness of credit allocation is related to financial conditions. Variations over time in the riskiness of credit allocation may happen for separate yet complementary reasons (see Figure 2.3 for a schematic representation of the main channels).

In the canonical view of the business cycle with financial frictions, the availability of credit to riskier, more vulnerable firms is procyclical, leading to a rise in the riskiness of credit allocation during economic expansions. A driver of fluctuations in the quantity and riskiness of credit is the time-varying effect of financing frictions attributable to changes in borrowers' net worth. Following a positive macroeconomic shock, or when interest rates fall, a firm's short-term prospects and its net worth—the difference between the economic value of its assets and its liabilities—increase, reducing the scope of problems related to asymmetries of information between lenders and borrowers, and allowing firms with high leverage easier access to credit markets. Conversely, following a negative shock, or when interest rates rise, firms with relatively weak balance sheets find it relatively harder to obtain credit (Bernanke and Gertler 1989; Kiyotaki and Moore 1997).[7]

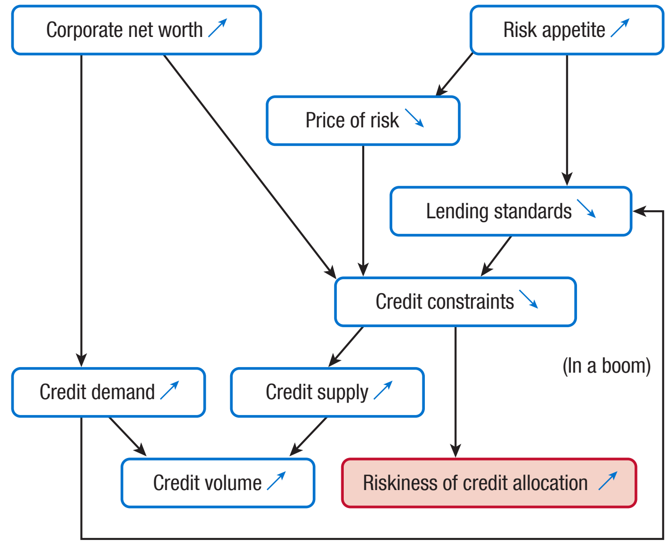
[7]Various versions of this mechanism are described in the so-called financial accelerator literature. In this literature, the relaxation of the borrowing constraints applies to all firms, not only to riskier ones. However, borrowing constraints are binding only for the riskiest

Fluctuations in credit quantity and the riskiness of credit allocation can also be driven by variations over time in investor beliefs, risk appetite, or perceptions of economic uncertainty, which directly affect credit spreads and expected volatility. In good times, those most optimistic about asset values can borrow extensively to acquire these assets, thereby pushing up asset prices. Following bad news, uncertainty and volatility rise, leading lenders to require higher margins, triggering deleveraging and fire sales (Geanakoplos 2010). To the extent that optimism is positively correlated with risk, this mechanism can also generate procyclical variations in the riskiness of credit allocation.[8] It is also possible that in good times investors form unduly optimistic beliefs about future economic prospects, leading them to extend credit to more vulnerable firms and allowing borrowers to increase their leverage excessively (Minsky 1977; Kindleberger 1978; Bordalo, Gennaioli, and Shleifer 2018). Finally, the risk appetite of financial intermediaries with long-term liabilities and short-term assets is likely to make them search for yield when monetary conditions are loose, resulting in riskier firms getting easier access to credit (Rajan 2006).

Banks' capacity and incentives to screen borrowers are likely to deteriorate in periods of significant credit expansions, reinforcing the procyclical nature of lending standards and of lending to relatively more vulnerable firms. The longer a credit expansion lasts, the lower the screening ability of the pool of loan officers becomes because of a loss of institutional memory about bad credit risks (Berger and Udell 2004). In addition, faced with the need to intermediate larger volumes of credit than usual during a credit boom, financial intermediaries do not find it profitable to properly screen borrowers or maintain lending standards (Dell'Ariccia and Marquez 2006).

Bank capital can also play an important role in determining the riskiness of credit allocation and its cyclicality through several channels. Banks gather and generate information about the creditworthiness of potential borrowers and thus can provide credit to firms that are too risky to tap financial markets directly. But banks' ability to raise funds to perform

Figure 2.3. Key Drivers of the Riskiness of Credit Allocation



Source: IMF staff.
Note: The diagram abstracts from the role of bank capital and leverage, feedback loops, and possible heterogeneity in credit demand.

this role also depends on their own capital levels. Thus, through this channel, an increase in bank capital may lead to an expansion of credit to firms with poorer fundamentals (Holmstrom and Tirole 1997).[9] Yet the relationship between short-term interest rates, bank leverage, and bank risk taking is ambiguous in theory, because it is the result of the combination of several effects that work in opposite directions (see Dell'Ariccia, Laeven, and Marquez 2014; Dell'Ariccia, Laeven, and Suarez 2017).[10]

The balance of these mechanisms will also determine how the riskiness of credit allocation relates to future

firms. Thus, relatively riskier firms benefit disproportionately from the cyclical relaxation of these constraints in good times.

[8]Caballero and Simsek (2017) argue that the degree of optimism is a critical state variable in the economy, not only because optimism has a direct impact on asset valuations, but also because it weakens the dynamic feedback between asset prices, aggregate demand, and growth.

[9]Such an increase can, at least in the short term, be the result of a positive macroeconomic or financial shock, which strengthens the asset side of banks' balance sheets. Adrian and Shin (2014) show that the Holmstrom and Tirole (1997) model translates into a model of procyclicality.

[10]Traditional portfolio allocation models predict that a higher interest rate on safe assets leads to a reallocation from riskier securities toward safe assets (Fishburn and Porter 1976). In contrast, risk-shifting models of monetary policy predict that an increase in the interest rate that banks must pay on deposits exacerbates the agency problem associated with limited liability and increases bank risk taking, especially for poorly capitalized banks (Matutes and Vives 2000). Finally, banks may be induced to switch to riskier assets with higher expected yields when monetary easing compresses their margins by lowering the yield on their short-term assets relative to that on their long-term liabilities, especially if they are poorly capitalized (Dell'Ariccia, Laeven, and Suarez 2017).

macro-financial stability. Directing an increased share of lending to riskier firms may be fully rational and profitable and reflect the normal functioning of a healthy financial system in some phases of the business and credit cycles, or it may reflect improvements in intermediaries' risk-management technologies. Alternatively, it may reflect poorer screening of borrowers, excessive risk taking (or neglect of risk), and misallocation of financial resources and may therefore have widespread detrimental consequences on the soundness of financial intermediaries and the economic performance of the economy down the road.[11] Furthermore, in the latter case, higher riskiness is much more a reflection of compositional shifts in lending toward riskier firms than a reflection of an aggregate buildup of leverage.

The Riskiness of Credit Allocation and Its Evolution across Countries

A first step in the chapter's analysis is the construction of new measures capturing the riskiness of corporate credit allocation.

- The riskiness of credit allocation cannot be assessed from aggregate macroeconomic or financial data because they do not reflect the heterogeneity of firms. The chapter builds on work by Greenwood and Hanson (2013) to construct such new measures based on various indicators of firm vulnerability for a set of 55 economies (26 advanced economies and 29 emerging market economies) over the 1991–2016 period using data for listed firms.[12]
- Four firm-level vulnerability indicators are considered to construct the measures. Methodologies for assessing default risk generally rely on accounting information or on a combination of accounting and market information.[13] In the chapter, several common accounting-based ratios are used to capture borrower vulnerability: the leverage ratio, the interest coverage ratio (ICR), and the debt-to-profit ratio (or debt overhang). All three ratios have a strong monotonic relationship with credit ratings (Moody's 2006). The ICR is also sometimes used as a proxy for a credit rating (for example, Damodaran 2014). A market-based indicator of credit risk, the expected default frequency (EDF), is also used.[14]
- Starting from information on a firm-level vulnerability indicator, a raw measure is computed as the average of this indicator among firms whose debt (the sum of loans and bonds) increases the most minus the average computed among firms whose debt increases the least—or declines the most. This raw measure is then transformed into the final measure by subtracting its country-specific mean to remove any influence of the country-specific sectoral composition and to ensure both cross-country and cross-measure comparability. An increase in the measure signals that the vulnerability of firms getting relatively more credit has risen relative to the vulnerability of firms getting relatively less credit. A positive (negative) value of the measure indicates that the riskiness of credit allocation is above (below) its country sample average. Box 2.1 provides a detailed explanation of how the measure is constructed and how to interpret its magnitude.[15]

The evolution of the riskiness of credit allocation across countries suggests clear global patterns (Figure 2.4). Its dynamic at the global level is broadly the same across the four borrower vulnerability indicators used. 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 2004, rose steeply during 2004–08, and hit a peak at the onset

[11]In addition, excessive borrowing is a source of negative externalities (see Farhi and Werning 2016 and references therein).

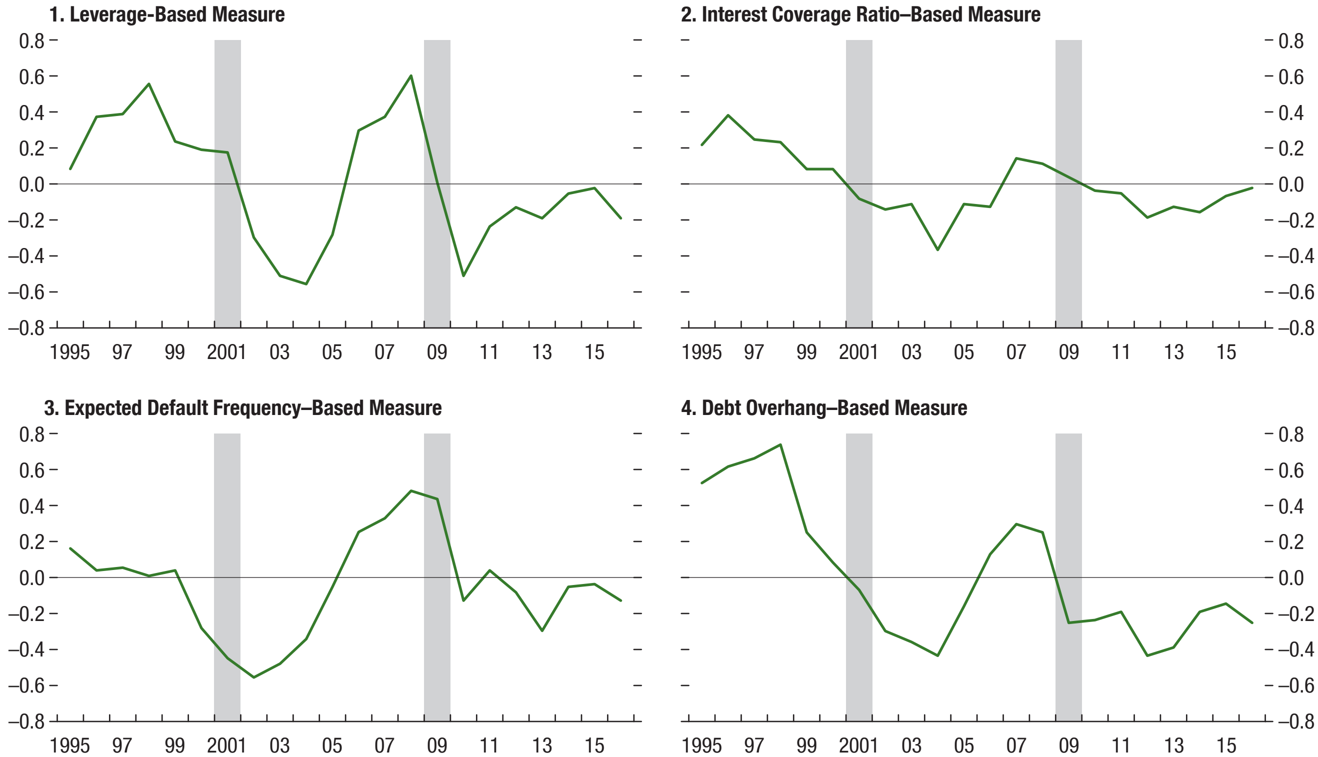
[12]Data are sourced from the Worldscope database, which provides a rich set of annual financial variables for listed firms. Annex 2.1 provides details on the sample and explanations on the data cleaning process.

[13]Scoring methods are based on a small set of accounting ratios. These include the *Z*-score (Altman 1968, 2013) and the *O*-score (Ohlson 1980). Other methods add market-based variables and use more advanced statistical techniques to compute relative weights (Shumway 2001; Campbell, Hilscher, and Szilagyi 2011). Other approaches have instead focused on using Merton's (1974) option pricing formula as the basis for modeling to construct measures of expected default frequency (such as Moody's KMV model). Credit rating agencies have designed sophisticated rating methodologies that also incorporate judgment (for example, Standard and Poor's 2013).

[14]In their study of credit quality in the United States, Greenwood and Hanson (2013) focus the core of their analysis on the EDF and demonstrate the robustness of their result when using leverage or the ICR. Acharya and others (2016) measure riskiness using the ICR. Banco de España (2017) includes leverage and the ICR in its small set of indicators aimed at capturing financial soundness. See Annex 2.1 for a precise definition of the firm-level indicators used in the chapter.

[15]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.

Figure 2.4. The Riskiness of Credit Allocation Is Cyclical at the Global Level
(Index; global median)



Sources: Worldscope; and IMF staff estimates.
Note: The panels show the simple two-year moving average of the median economy in the unbalanced subsample. Shaded areas indicate periods during which global real GDP growth was less than 2.5 percent. See Annex 2.1 for the list of economies included in the analysis.

of the global financial crisis. It then declined sharply over the next two years and was slightly below its precrisis level at the end of 2016, the latest available data point.

This global dynamic is reflected at the country level, with some country-specific nuances. Figure 2.5 shows the evolution of the riskiness of credit allocation in eight major economies using the leverage-based measure and the EDF-based measure during 1995–2016. The two measures display similar patterns in the first six countries, but sometimes provide contrasting signals in the last two countries, documenting a degree of complementarity across measures in some countries or periods:[16]

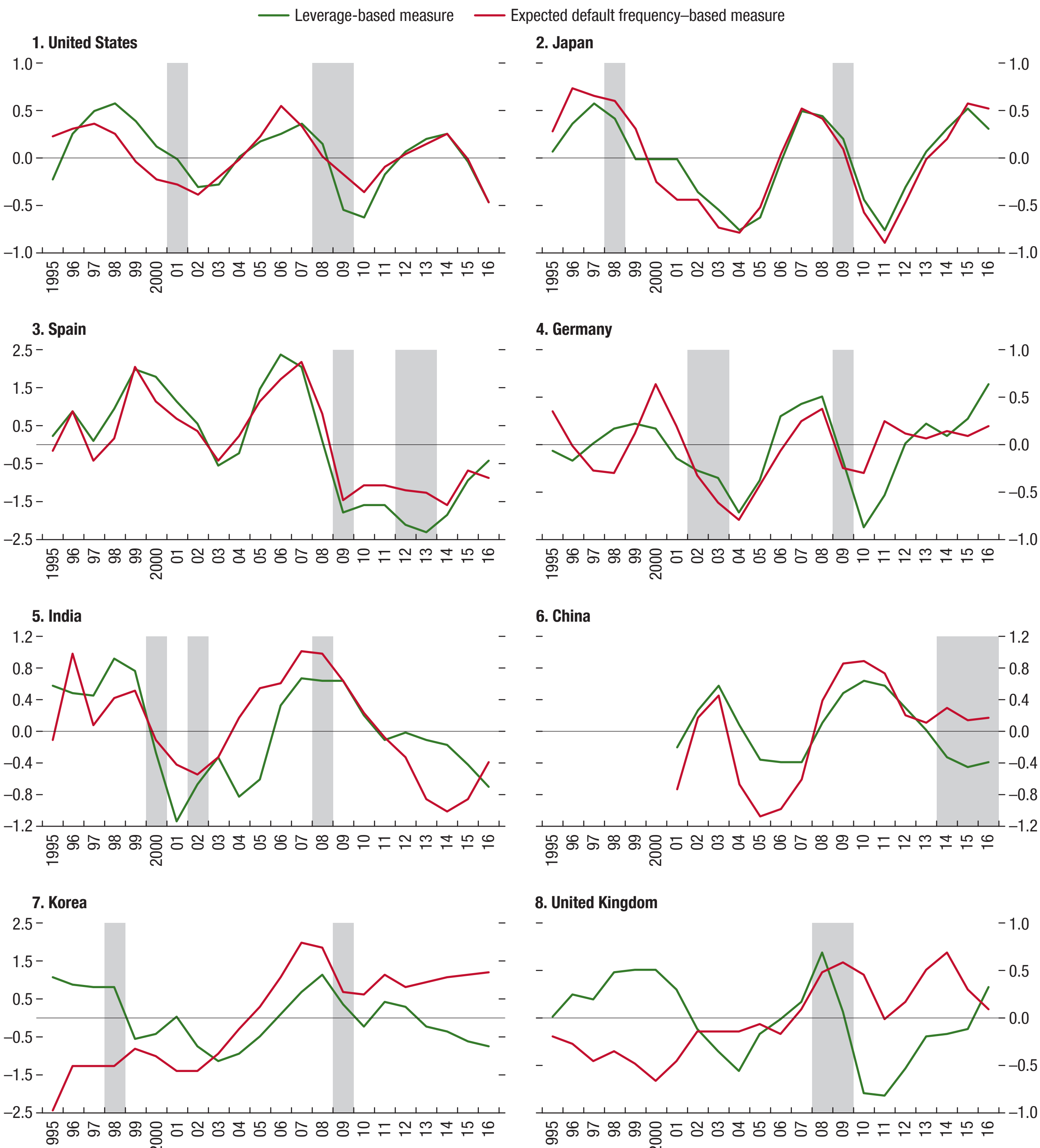
- The dynamics in the United States (Figure 2.5, panel 1) and Japan (Figure 2.5, panel 2) are very similar in both cyclicality and magnitude.[17] The most recent period (2014–16), however, suggests a divergence: the riskiness of credit allocation decreased in the United States to a relatively low level, while in Japan it remained at a level that is relatively high in historical perspective.[18]
- Figure 2.5, panels 3 and 4, show contrasting developments in two of the largest euro area countries. Spain (Figure 2.5, panel 3) had a credit boom

[16]While the correlation of the four measures is generally high, it is the smallest between the leverage-based and the EDF-based measures.

[17]The pattern in the United States closely resembles that in Greenwood and Hanson (2013). 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.

[18]In the United States, corporate leverage increased across the board during 2010–16. Since increases are similar across groups of firms, the relative comparisons between groups used in this chapter to track the distribution of credit allocation may not rise over this period (see Box 2.1).

Figure 2.5. Selected Economies: Riskiness of Credit Allocation, 1995–2016
(Index)



Sources: Worldscope; and IMF staff estimates.
Note: The panels show the simple two-year moving average. Shaded areas indicate periods of growth below the 15th percentile of the growth distribution. See Box 2.1 for details on the construction of the measures.

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 the findings of Banco de España (2017) mentioned in the introduction to the chapter. By contrast, variations in the riskiness of credit allocation in Germany (Figure 2.5, 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 2.5, panel 5) has broadly followed global patterns, and the measure was at a relatively low level in 2016. The synchronization of China (Figure 2.5, 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). Most of the recent literature on credit allocation in China has focused on the link between credit and firm-level productivity of capital (or profitability) rather than firm-level credit risk. Using China as an example, Box 2.2 illustrates how a set of new profitability-based indicators, constructed similarly to the new vulnerability indicators discussed in the core of this chapter, can provide additional insights into the quality of credit allocation.
- Developments in Korea (Figure 2.5, panel 7) highlight that only the accounting-based measure indicated high riskiness before this country's crisis in the late 1990s. The EDF-based measure, constructed using equity market information, does not signal any potential problem related to the riskiness of credit allocation at that time, suggesting that equity market investors were too optimistic and that accounting-based measures better reflected fundamentals. Also, the two measures point in different directions in recent years, with the leverage-based measure at a low level at the end of 2016. As in Korea, there is a disconnect between the dynamics of the two measures for the United Kingdom (Figure 2.5, panel 8) during the 1990s and the 2010s. This disconnect could be due to the effect of the volatility of firm-level equity prices on the EDF-based measure but is a little puzzling given the depth of financial markets in that country. Nonetheless, the two measures point to rising riskiness of credit allocation before the global financial crisis in Korea and the United Kingdom.

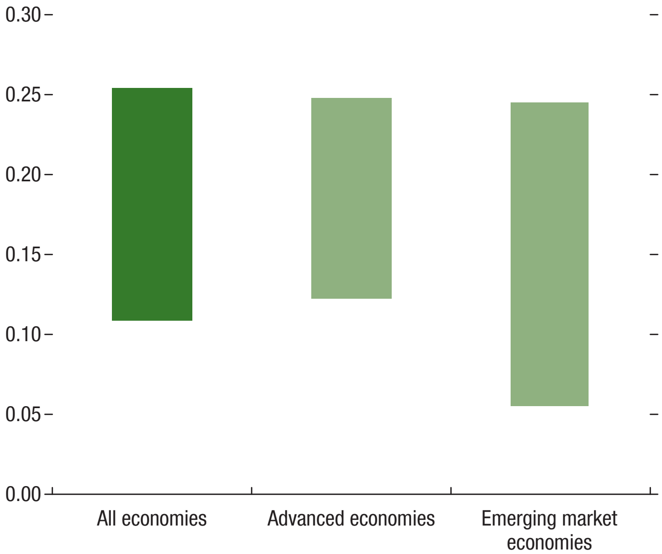
These patterns raise several questions regarding the cyclicality of the riskiness of credit allocation. Does it systematically rise when GDP growth and credit growth are strong? If so, does this increase depend on other measures of financial conditions that can signal expansions in credit supply, such as credit spreads or a broad financial conditions index? To shed light on these questions, the econometric analysis that follows focuses on the relationship between the riskiness of credit allocation, the state of the business cycle, and financial conditions using standard cross-country panel regressions (see Annex 2.1 for data sources and Annex 2.2 for details on methodology).

Periods of faster economic and credit expansion are associated with riskier credit allocations. Regression analysis indicates that the riskiness of credit allocation is procyclical: it increases when GDP growth or changes in the domestic credit-to-GDP ratio are stronger. The first finding is consistent with standard financial accelerator mechanisms, and the second points to mechanisms in which credit supply shocks affect macro-financial outcomes through a risk-taking channel. The association of credit expansion with greater riskiness of credit allocation is statistically significant for all four 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 exact measure (Figure 2.6). Results are similar for advanced and emerging market economies, although the dispersion of the estimated relationship is larger in the latter, most likely because of their smaller sample size.

The association between larger credit expansions and riskier allocations is stronger when financial con-

Figure 2.6. The Riskiness of Credit Allocation Rises When a Credit Expansion Is Stronger

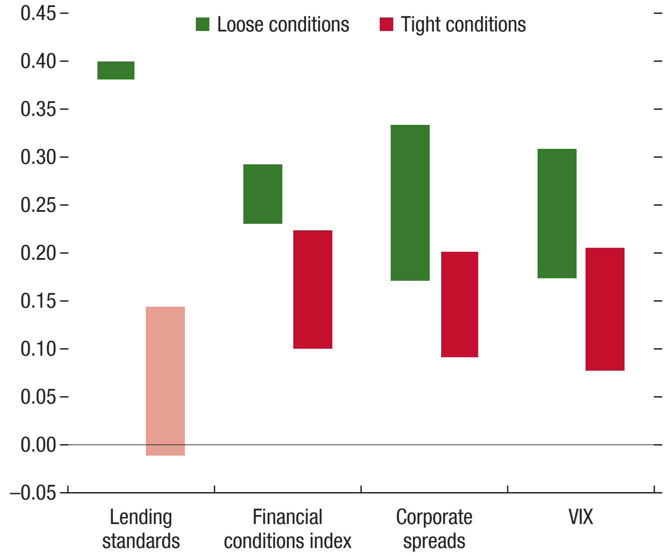
(Standard deviations of the riskiness of credit allocation)



Sources: Worldscope; and IMF staff estimates.
Note: The figure shows the range of impact of a contemporaneous increase in the change in the credit-to-GDP ratio by one standard deviation on the four (leverage-, interest coverage ratio–, debt overhang–, and expected default frequency–based) measures of the riskiness of credit allocation. Dark-colored (light-colored) bars indicate that the effects are statistically significant at the 10 percent level or higher for four (three) measures out of four. See Annex 2.2 for details on methodology.

Figure 2.7. The Association between the Size of a Credit Expansion and the Riskiness of Credit Allocation Is Greater When Lending Standards and Financial Conditions Are Looser

(Standard deviations of the riskiness of credit allocation)



Sources: Worldscope; and IMF staff estimates.
Note: The figure shows the range of impact of a contemporaneous increase in the change in the credit-to-GDP ratio by one standard deviation on the four (leverage-, interest coverage ratio–, debt overhang–, and expected default frequency–based) measures of the riskiness of credit allocation when lending standards or financial conditions (financial conditions index, corporate spreads, and VIX) are "loose" or "tight." The level of a variable is defined as loose (tight) when it is equal to the 25th percentile (75th percentile) of its distribution. Dark-colored (light-colored) bars indicate that the effects are statistically significant at the 10 percent level or higher for four (one) measures out of four. See Annex 2.2 for details on methodology. VIX = Chicago Board Options Exchange Volatility Index.

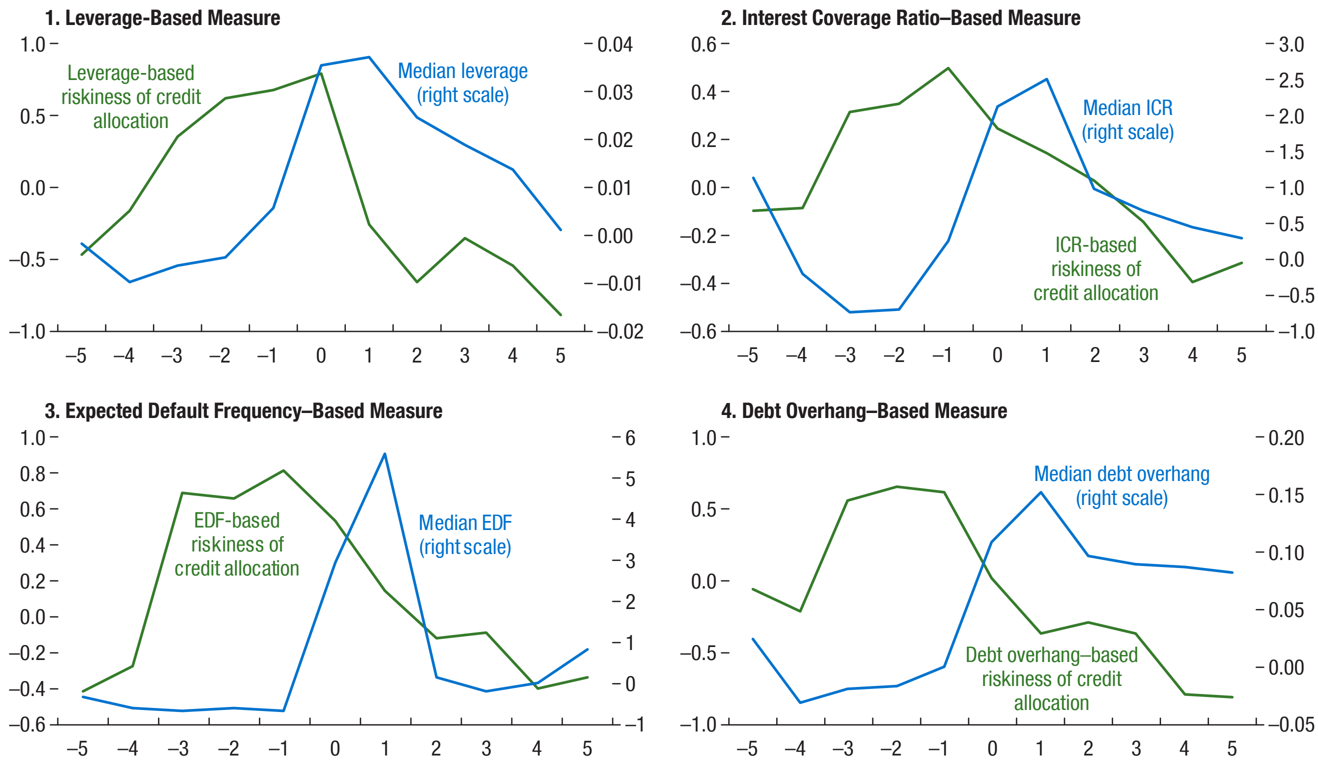
ditions are loose. A credit expansion accompanied by loose financial conditions or loose lending standards is more likely to be driven by shifts in credit supply and higher risk appetite of financial intermediaries. Regression analysis provides evidence of such a channel: both variables amplify the cyclicality of the riskiness of credit allocation. Specific components of financial conditions appear to matter more than others. In particular, low corporate credit spreads (or high global risk appetite, proxied by the Chicago Board Options Exchange Volatility Index [VIX]) during credit expansions result in allocations that are riskier than those observed when the expansions are accompanied by high credit spreads (or low global risk appetite) (Figure 2.7). Furthermore, a higher stock market price-to-book ratio is associated with a higher level of the riskiness of credit allocation. Additional analysis studying the joint dynamics of the riskiness of credit allocation, financial conditions, credit expansions, and economic growth using a panel vector autoregression confirms these findings and shows a significant effect of financial conditions on the riskiness of credit allocation (Box 2.3).[19]

These trends and properties of the riskiness of credit allocation are generally confirmed when using a different sample that covers both listed and unlisted firms. The robustness of the results discussed above is checked by constructing similar measures using data that cover a wider universe of firms (both listed and unlisted), but for a smaller set of countries and over fewer years.[20] The similarity is very reassuring considering the significant differences in the cross-sectional coverage of the two databases.

[19]Measurement of these effects assumes that the financial conditions index responds contemporaneously to all other variables, while the riskiness of credit allocation responds with a lag.

[20]This robustness analysis is based on the Orbis database and covers only 50 economies from 2000. See Annex 2.1 for details.

Figure 2.8. The Riskiness of Credit Allocation Rises to a High Level before a Financial Crisis, and Falls to a Low Level Thereafter
(Index; median across all crisis episodes; 11-year window)



Sources: Laeven and Valencia (forthcoming); Worldscope; and IMF staff estimates.
Note: Systemic banking crises are defined as in Laeven and Valencia (forthcoming). The crisis occurs at time 0. Data are demeaned at the country level. The panels show the median across all crisis countries in a balanced panel. The riskiness measures are constructed as explained in Box 2.1. Median leverage (EDF) refers to the median of the firm-level leverage (EDF) variable. Median ICR refers to the negative of the median of the firm-level ICR. Median debt overhang refers to the negative of the median of the EBITDA-to-debt ratio. EBITDA = earnings before interest payments, taxes, depreciation, and amortization; EDF = expected default frequency; ICR = interest coverage ratio.

The Riskiness of Credit Allocation and Macro-Financial Stability

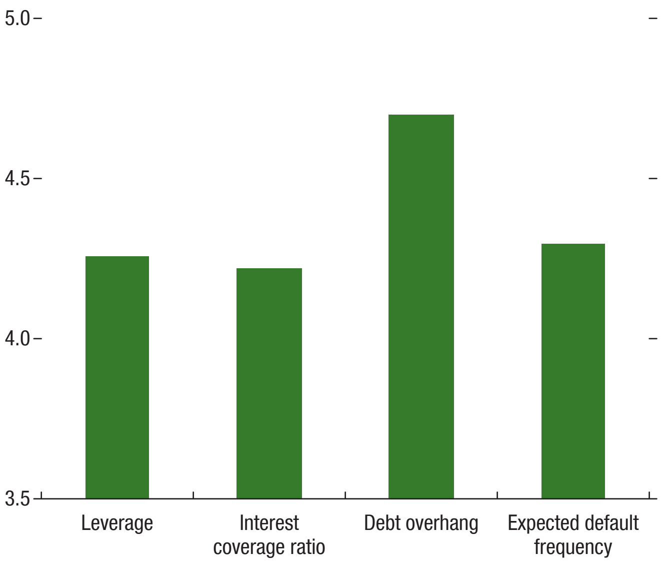
Does the riskiness of credit allocation help predict episodes of financial instability and downside risks to growth? To answer these questions, the econometric analysis builds on the existing empirical literature on the determinants of risks to the financial sector and real activity, and augments the literature's specifications with the riskiness of credit allocation. Specifically, using cross-country regressions, this section analyzes whether this new measure constitutes an early warning indicator of a systemic financial crisis and of banking sector stress, and whether it is a predictor of low realizations of future GDP growth.[21] Information on the econometric framework is provided in Annex 2.3.

The riskiness of credit allocation has a very clear inverted-U shape around systemic financial crisis episodes. The dynamic of the riskiness of credit allocation in the period at the start of a crisis is unambiguous: it rises gradually during the five years preceding the crisis, reaches a relatively high level, and then falls following the onset of the crisis. This is true regardless of the firm-level indicator chosen to construct the riskiness measure (Figure 2.8). Interestingly, the riskiness of credit allocation signals a forthcoming crisis much better than

[21]The results described in this section are robust to the inclusion of standard corporate vulnerability indicators, such as median firm leverage, and to the inclusion of a measure of the high-yield share of bond issuance. The results, however, are weaker if the post-2008 period is excluded from the sample. The analysis of predictive performance is in-sample (all available observations are used to estimate the models).

Figure 2.9. Higher Riskiness of Credit Allocation Signals Greater Risk of a Systemic Banking Crisis

(Proportional increase in the odds of a banking crisis)



Source: IMF staff estimates.
Note: The figure shows the multiplicative effect of a one standard deviation increase in the riskiness of credit allocation on the odds of a systemic banking crisis, as defined in Laeven and Valencia (forthcoming). See Annex 2.3 for methodology.

Figure 2.10. Higher Riskiness of Credit Allocation Signals Greater Risk of Banking Sector Stress

(Proportional increase in the odds of banking sector stress)

Source: IMF staff estimates.
Note: The figure shows the multiplicative effect of a one standard deviation increase of the riskiness of credit allocation on the odds of bank equity stress in a time window from t to $t + h$, in which $h = 0, 1, 2, 3$. Bank equity stress is defined as annual bank equity excess return over the short-term government bond yield that is lower than the country-specific mean by at least one standard deviation. Each bar shows the minimum and maximum effects across the four (leverage-, interest coverage ratio–, debt overhang–, and expected default frequency–based) measures. Dark-colored (light-colored) bars indicate that the effects are statistically significant at the 10 percent level or higher for four (two) measures out of four. See Annex 2.3 for methodology.

the underlying conventional corporate vulnerability indicators when considered individually (see the blue lines in Figure 2.8): these more traditional indicators pick up significantly only when the crisis has already struck.

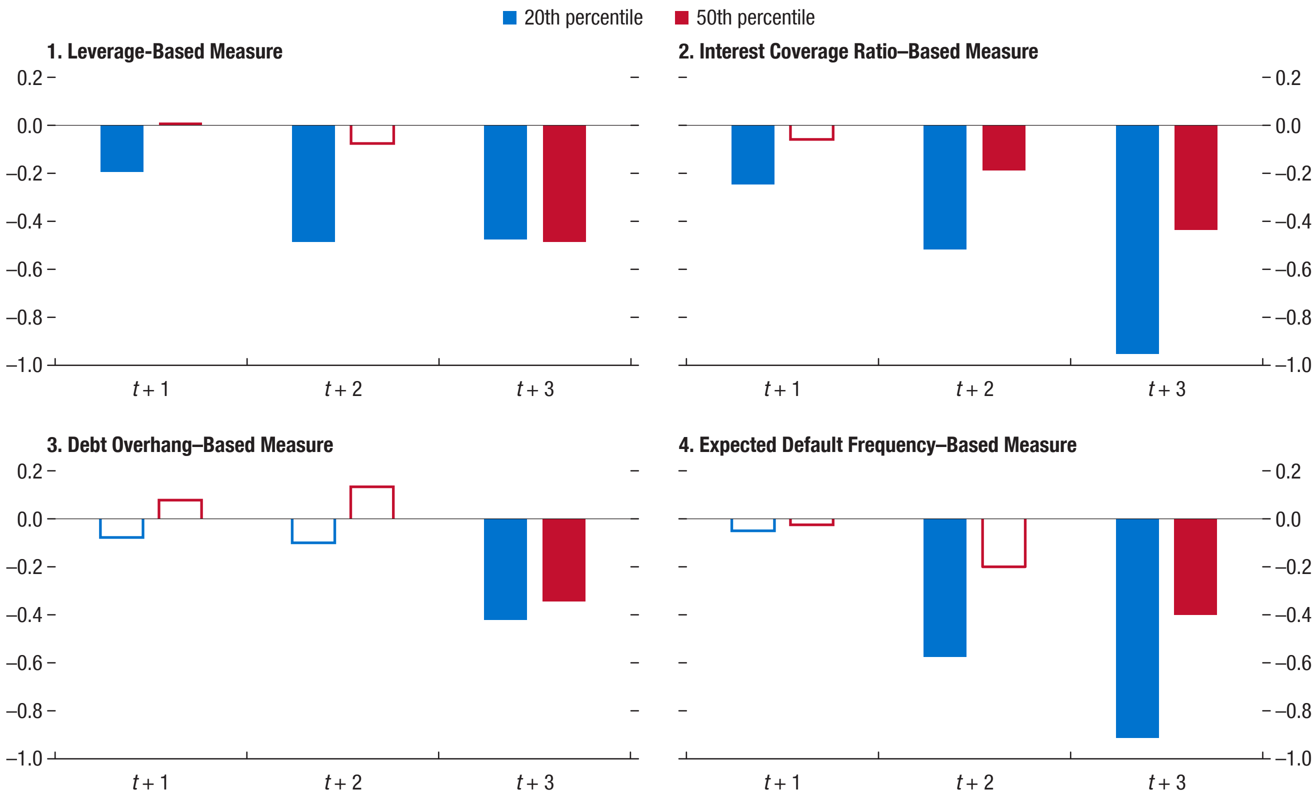
Regression analysis confirms that a greater riskiness of credit allocation increases the odds of a future systemic banking crisis (Figure 2.9). The effect in the crisis model is measured in addition to the effect of the change in credit volumes, which has been emphasized in the literature, and the effect of financial conditions. Thus, for a given size of credit expansion, a greater riskiness of credit allocation implies a higher probability of a financial crisis. A one standard deviation increase in the riskiness measure increases the odds of a crisis by a factor of about four.[22] The gain in explanatory power when adding the riskiness variable, between 11 and 25 percentage points, is also reasonably large.

The riskiness of credit allocation also helps forecast banking sector equity stress up to three years in advance. Because the identification and timing of the occurrence of a systemic financial crisis are somewhat subjective and crises are rare events, it is useful to seek confirmation of the results obtained in a crisis model by using a banking sector equity stress model for which the number of events is larger and the timing is completely objective.[23] Regression analysis shows that the riskiness of credit allocation adds predictive power to such a model for any horizon from zero to three years (Figure 2.10). A one standard deviation increase in the riskiness of credit allocation increases the odds by a factor of 1.3 to 2, making banking sector stress up

[22]The odds of a crisis refer to the ratio of the probability of observing a crisis to the probability of not observing it. For instance, in the sample used in the estimation, the probability of observing a crisis is about 5 percent. Thus, the probability of not observing a crisis is about 95 percent, and the odds of a crisis are 5.3 percent (100*5/95). A fourfold increase from this level would raise the odds to 21 percent.

[23]A banking sector equity stress episode occurs when the annual excess equity return of the banking sector is lower than the country-specific mean by at least one standard deviation. Such episodes are relevant for macro-financial stability because they are typically followed by significant negative credit supply shocks, which, in turn, can translate into declines in economic activity and employment.

Figure 2.11. Higher Riskiness of Credit Allocation Signals Higher Downside Risks to GDP Growth
(Percentage points of GDP growth)



Source: IMF staff estimates.
Note: The panels show the impact of a one unit increase in the riskiness of credit allocation on the 20th and 50th percentiles of the distribution of future cumulative GDP growth from year t to year $t + h$, with $h = 1, 2, 3$. Solid colored bars indicate that the effects are statistically significant at the 10 percent level or higher. An empty bar indicates absence of statistical significance. See Annex 2.3 for methodology.

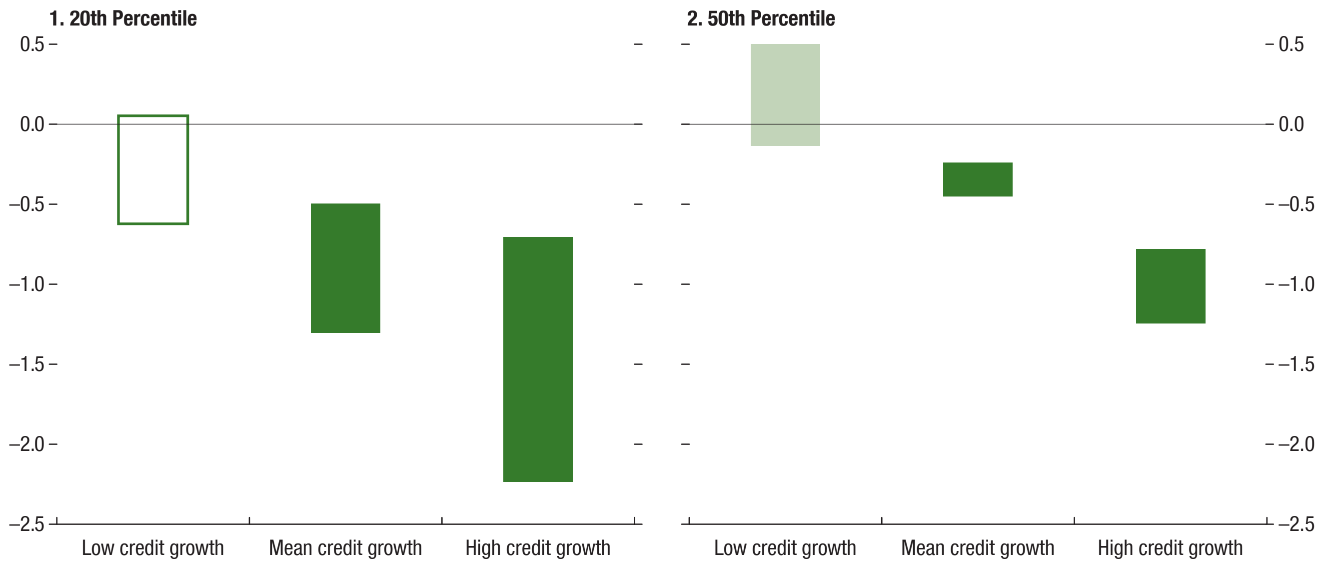
to two times more likely, depending on the measure and the horizon.

A riskier credit allocation signals downside risks to growth in the short to medium term. The analysis examines the predictive power of the riskiness of credit allocation on two percentiles (20th and 50th) of cumulative real GDP growth one to three years into the future.[24] The riskiness of credit allocation is strongly related to the median and left tail of the growth distribution over all horizons. In line with the findings described previously on banking sector stress risk, the new measure provides information on downside risks to growth over the short to medium term (Figure 2.11). These effects are in addition to those of changes in the credit-to-GDP ratio and financial conditions. The effect on the downside risks to growth is significant when measures of the riskiness of credit allocation are constructed based on a sample that covers unlisted as well as listed firms.

The effects of a riskier credit allocation complement those of credit expansions on growth-at-risk over the medium term. One might expect that credit booms that are accompanied by a rise in the riskiness of credit allocation pose stronger downside risks to growth than those that are not. The analysis indicates that they do. This simultaneous rise in credit volumes and riskiness signals elevated risks to growth two and three years ahead. This finding is consistent with recent evidence showing that an increase in the high-yield share of bond issuance in advanced economies during credit booms is associated with lower future mean GDP growth (see Box 2.4 and Kirti 2018).

[24]The approach builds on Adrian, Boyarchenko, and Giannone (2016) and Chapter 3 of the October 2017 GFSR.

Figure 2.12. The Association of the Riskiness of Credit Allocation with Downside Risks to GDP Growth Depends on the Size of Credit Expansion
(Percentage points of GDP growth)



Source: IMF staff estimates.
Note: The panels show the range of impact of a one unit increase in the riskiness of credit allocation on the 20th and 50th percentiles of the distribution of future cumulative GDP growth from year t to year $t + 3$ across the four (leverage-, interest coverage ratio–, debt overhang–, and expected default frequency–based) measures. The impact is conditional on high, mean, and low credit growth. High (low) credit growth is defined as one standard deviation above (below) mean credit growth. Dark-colored (light-colored) bars indicate that the effects are statistically significant at the 10 percent level or higher for four (two) out of four measures. An empty bar indicates no statistically significant impact of any of the four measures. Further details on the methodology are in Annex 2.3.

Conversely, during credit contractions or relatively soft credit expansions, a higher riskiness of credit allocation does not increase downside risks to future GDP growth. When the change in the credit-to-GDP ratio is well below its historical average—for example, in the aftermath of a recession or a creditless recovery—the association between higher riskiness of credit allocation and downside risks to GDP growth is weaker, and its sign can reverse if the credit expansion is sufficiently weak. Figure 2.12 shows that at a three-year horizon, when the change in the credit-to-GDP ratio is low by historical standards, an increase in risk taking has no significant impact on downside risks to growth. This finding indicates that a rise in the riskiness of credit allocation is harmless in some phases of the cycle.

The Role of Policy and Structural Factors

Having established that the riskiness of credit allocation is a vulnerability indicator, the chapter now turns to an analysis of more structural determinants of its level and cyclicality. Three sets of variables—banking sector soundness, macroprudential policies, and selected aspects of the supervisory, legal, and institutional frameworks—come into play. The determinants of the level and credit cyclicality of the riskiness of credit allocation vary somewhat depending on which underlying firm-level vulnerability indicator is used. The analysis that follows focuses on determinants whose robustness is apparent across all four measures.[25] The quantitative effects of these structural determinants on the cyclicality of the riskiness of credit allocation are summarized in Figure 2.13.

Bank capital appears to have little significant effect on the cyclicality of the riskiness of credit allocation. Recent empirical studies on how bank capital

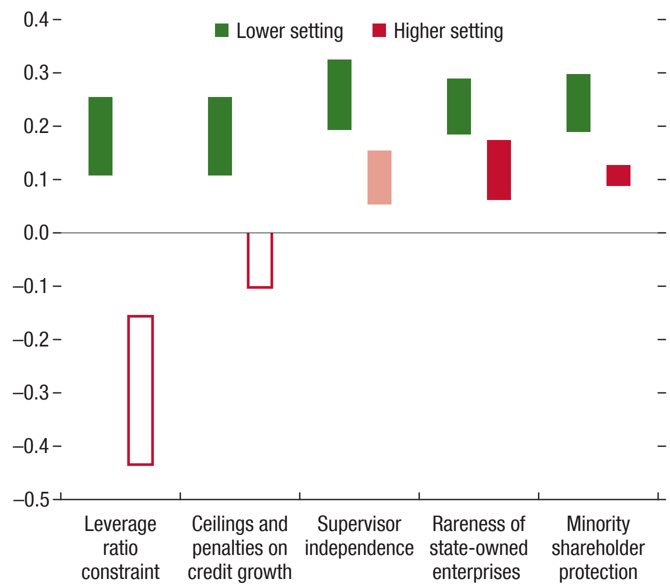
[25]The effect on the credit cyclicality of the riskiness of credit allocation is estimated through an interactive term between the policy or institutional variable and the change in the credit-to-GDP ratio. Variables capturing financial sector depth and financial openness are not found to have any robust effect across measures and are therefore omitted from the discussion. A finding is defined as robust when the regression coefficient is significant for at least two of the four measures and when the sign is identical across all four measures. Consistency of the signs of the effects in level and in interaction is also required. See Annex 2.1 for definitions of the variables and Annex 2.2 for methodology.

affects the relationship between financial conditions and credit flows to risky firms provide contrasting results.[26] This literature indicates that the link between credit conditions, firm riskiness, and bank risk taking is likely to depend on country circumstances. Therefore, it may not be surprising that only suggestive evidence is found that conventional measures of banking system capitalization or leverage matter for the cyclicality of the riskiness of credit allocation: greater buffers are generally associated with greater cyclicality of the riskiness of credit allocation, but not in a robust manner.

However, macroprudential policy tightening reduces the cyclicality of the new vulnerability measure. An increase in regulatory capital requirements curtails domestic banks' risk-bearing capacity by reducing the availability of free capital that banks can use to provide loans. Regression analysis confirms that tightening of the macroprudential policy stance dampens the increase in the riskiness of credit allocation associated with faster credit growth. The result holds for changes in minimum leverage ratio and changes in ceilings and penalties related to credit growth.[27] Increases in capital conservation buffers also reduce the level of the riskiness of credit allocation. The capital conservation buffer and the minimum leverage ratio are policy instruments that were introduced as part of the regulatory changes following the global financial crisis. The findings of the chapter thus suggest that postcrisis regulatory tightening has had an impact on the evolution of the riskiness of credit allocation and has played a role in limiting the size of the rebound in the measure documented in Figure 2.4.[28]

Greater supervisory independence is associated with reduced cyclicality of the riskiness of credit allocation. A more independent supervisor is likely to be more empowered to exert its oversight throughout the financial cycle. Accordingly, when the supervisory authority enjoys greater legal protection from the banking industry, the quality of credit allocation is less sensitive to domestic credit growth.

Figure 2.13. The Association of a Credit Expansion with the Riskiness of Credit Allocation Depends on Policy and Institutional Settings
(Standard deviations of the riskiness of credit allocation)



Sources: Worldscope; and IMF staff estimates.
Note: The figure shows the range of impact of a contemporaneous increase in the change in the credit-to-GDP ratio by one standard deviation on the four (leverage-, interest coverage ratio–, debt overhang–, and expected default frequency–based) measures of the riskiness of credit allocation when policy and institutional settings (leverage ratio constraint, ceiling and penalties on bank credit growth, independence of supervisory authority from banks, rareness of state-owned enterprises, and minority shareholder protection) are at a "lower" setting or a "higher" setting. A lower (higher) setting for macroprudential policy means no policy change (one tightening action during the year). A lower (higher) setting for the other variables means a level equal to the 25th percentile (75th percentile) of their distribution. Dark-colored (light-colored) bars indicate that the effects are statistically significant at the 10 percent level or higher for four (three) measures out of four. Empty bars indicate that the effects are statistically insignificant at the 10 percent level for the four measures. See Annex 2.2 for details on the methodology.

[26]On the one hand, Jiménez and others (2014) show that in Spain during 2002–08 a lower overnight interest rate induced relatively less capitalized banks to grant more loan applications and to commit larger loan volumes to risky firms. Acharya and others (2016) find that, in contrast with relatively highly capitalized banks, relatively less capitalized banks in the euro area increased their lending to very risky firms following the European Central Bank's announcement in 2012 that it stood ready to conduct Outright Monetary Transactions. On the other hand, Dell'Ariccia, Laeven, and Suarez (2017) find evidence consistent with traditional risk shifting by less capitalized banks, while Schivardi, Sette, and Tabellini (2017) find that undercapitalized banks were less likely to cut credit to zombie firms during the recent crisis years in Italy.

[27]Tightening of minimum capital requirements is found to be associated with a nonrobust increase in the riskiness of credit allocation, suggesting reverse causality. Loan provisioning requirements are not found to have any significant effects, either in level or when interacted with the change in the credit-to-GDP ratio. Jiménez and others (2017) and Uluc and Wieladek (2017) provide evidence that tightening capital or provisioning requirements can result in greater risk taking by banks.

[28]Only one change in minimum leverage requirements was implemented before the global financial crisis in the sample. Changes to ceilings and penalties related to credit growth occur in only four countries in the sample.

The sensitivity of the riskiness of credit allocation to domestic credit growth also responds to some aspects of the institutional and legal environments. A smaller government footprint in the nonfinancial corporate sector reduces the cyclicality of the new measure. Greater protection of minority shareholders has an effect in the same direction. This latter finding highlights the importance of sound corporate governance frameworks for financial stability, as documented in Chapter 3 of the October 2016 GFSR.

Conclusions and Policy Implications

A riskier credit allocation is a source of vulnerability that may threaten financial stability. Policymakers and supervisors should pay close attention to its evolution. Both the volume and allocation of credit matter for financial stability. A period of high credit growth is more likely to be followed by a severe downturn or financial sector stress over the medium term if it is accompanied by an increase in the riskiness of credit allocation. Thus, while policymakers should be alert to periods of rapid credit expansion or increasing riskiness of credit allocation, they should pay special attention when they take place together. Supervisors should monitor credit origination standards and the riskiness of credit allocation on a continuous basis, intensify supervisory scrutiny during episodes of large credit expansion and loose financial conditions, and require corrective action if needed.[29]

The riskiness of credit allocation can be measured using firm-level financial statement data that are available in many countries and used for financial surveillance. The measures of the riskiness of credit allocation constructed for this chapter exploit cross-sectional information on firm-level net debt issuance and firm-level vulnerability. Several firm-level indicators of vulnerability (including leverage, interest coverage ratio, debt overhang, and expected default frequency) can be used to construct a measure. Each is suitable to specific country and data environments. The measures are simple to compute and can be readily used for macro-financial surveillance. Of course, the usefulness of these indicators for surveillance purposes will depend on the speed with which the underlying data become available. It is important, therefore, that policymakers engage in efforts to collect these granular data as swiftly as possible.[30]

Various institutional and policy settings may help policymakers tame the increase in the riskiness of credit allocation that occurs during large credit expansions. A more independent banking supervisor can better exert control over lending and origination standards during good times, when risks appear contained. Sounder corporate governance standards—which may reduce the ability of vulnerable firms' managers to "gamble for resurrection" or engage in pet projects—should be promoted. And several macroprudential policies, such as the tightening of some regulatory capital requirements, may reduce the ability or willingness of banks to lend to vulnerable firms.[31] Furthermore, policymakers could also address the potential consequences of an increase in the riskiness of credit allocation during a period of strong credit growth through increased provisioning requirements and thicker countercyclical capital buffers. The calibration of capital buffers should arguably consider the riskiness of credit allocation.[32] Finally, policies aimed at directing credit to certain firms or sectors of the economy without due consideration of underlying credit risk should be discouraged in periods of strong credit growth.

The riskiness of credit allocation at the global level has rebounded since its post-global-financial-crisis trough and was back to its historical average at the end of 2016. The relatively mild credit expansion in recent years, combined with postcrisis regulatory tightening, contributed to a softer rebound in the riskiness of credit allocation than might be expected given the very loose financial conditions. However, global patterns hide relevant country-level heterogeneity, and the rise of the riskiness of credit allocation in certain

[29]In periods when credit is stagnant or falling, a higher riskiness of credit allocation is less of a vulnerability.

[30]Financial statement data for domestically listed firms is often available to policymakers quarterly or semiannually. Therefore, policymakers in many countries should be able to easily construct the measures introduced in the chapter for their own country with shorter lags and at higher frequency than those reported in the chapter based on internationally comparable data.

[31]The evidence provided in the chapter is tentative. Further research needs to be performed to better understand the effect of macroprudential policy on the riskiness of credit allocation.

[32]Exploring issues related to calibration and timing of macroprudential policy actions as well as associated GDP growth trade-offs are, of course, essential and should be concrete next steps in the analysis. In particular, delving into the role thicker capital buffers could play in improving macro-financial outcomes following a rise in the riskiness of credit allocation to a high level would seem warranted.

countries has been more pronounced. As financial conditions loosened further in 2017, the riskiness of credit allocation might have continued to rise, which warrants close monitoring and heightened vigilance. Furthermore, relatively low credit allocation riskiness is not inconsistent with a large increase in conventional corporate vulnerability indicators, such as average leverage, as has been observed in some major economies in recent years. Finally, while this chapter focuses on the corporate sector, the riskiness of credit allocation to households may also be relevant and may not necessarily follow the same patterns. Monitoring this dimension of credit allocation is difficult, especially for a broad set of countries, but evidence from selected household surveys reported in the October 2017 GFSR suggests that the indebtedness of lower-income, more vulnerable households has increased in recent years in various countries.

Box 2.1. Measuring the Riskiness of Credit Allocation

The chapter measures the riskiness of credit allocation using the approach proposed by Greenwood and Hanson (2013). The measure is constructed for four different firm-level vulnerability indicators—leverage (total debt to total assets), debt overhang (total debt to earnings before interest, taxes, depreciation, and amortization [EBITDA]), interest coverage ratio (ICR; EBITDA to interest expenses), and expected default frequency.

For each firm-level vulnerability indicator, the measure is built as follows: first, for every 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 vulnerability. Second, firms are similarly sorted by the changes in net debt to lagged total assets into five equal-size bins. Firms in the bin with the largest increases in debt are called "top issuers," and firms in the bin with the largest decreases in debt are the "bottom issuers." Finally, the measure is computed as the difference between the average vulnerability decile for the top issuers and the corresponding average for the bottom issuers.

Changes in the measure over time help answer the following question: what is the evolution of the vulnerability profile of firms that are accumulating debt the fastest relative to that of firms that are reducing debt the fastest? The sign of the measure for some indicators is adjusted so that it rises when the vulnerability of firms whose total debt issuance is the largest is increasing.[1] Figure 2.1.1 summarizes this computation process graphically.

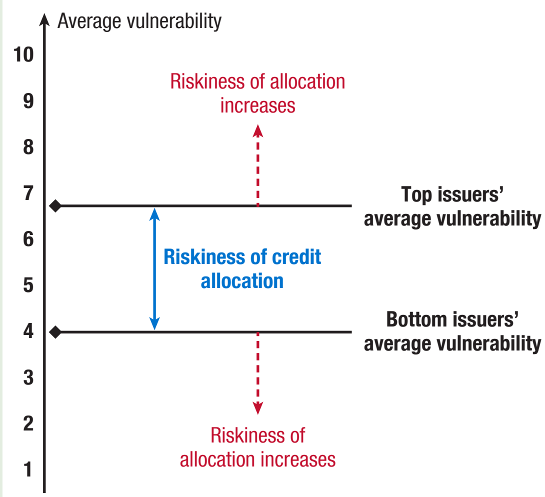
An example might be useful to provide a better understanding of the measure. Suppose that firm leverage increases by 5 percentage points for all firms and that firm-level issuance increases in equal proportion. Mean leverage will increase by 5 percentage points, but the measure of allocation riskiness will not change. Conversely, if leverage increases by 5 percentage points for top issuers, decreases by 5 percentage points for bottom issuers and remains unchanged for all other firms, mean leverage will not change, but the measure of allocation riskiness will rise.

Because it abstracts from changes in the mean and shape of the distribution of the vulnerability indicator, only the ranking of a firm in the distribution of that indicator matters. The measure is computed for all country-year pairs that meet minimum sample size requirements (see Annex 2.1). It reflects the broadest possible measure of debt (notably, it includes both loan and bond financing) and is therefore not affected by secular shifts in the relative size of bond and loan markets. It also reflects the continuous nature of firm vulnerability and default risk.

Using deciles rather than the raw values of a vulnerability indicator provides several advantages: it minimizes the influence of outliers, avoids the possibility of picking up secular trends, makes the comparison across measures based on different indicators straightforward, and provides a way to normalize the measure across countries. A downside of transforming into deciles is that information about changes in the cross-sectional dispersion of the indicator is lost.

Figure 2.1.2 presents information on the distribution of the four measures, which helps give a sense of their magnitude in the sample. Because the focus of the chapter is on the dynamics of the riskiness of credit allocation within countries and not on its variation across countries, the measures are demeaned at

Figure 2.1.1. Measuring the Riskiness of Credit Allocation



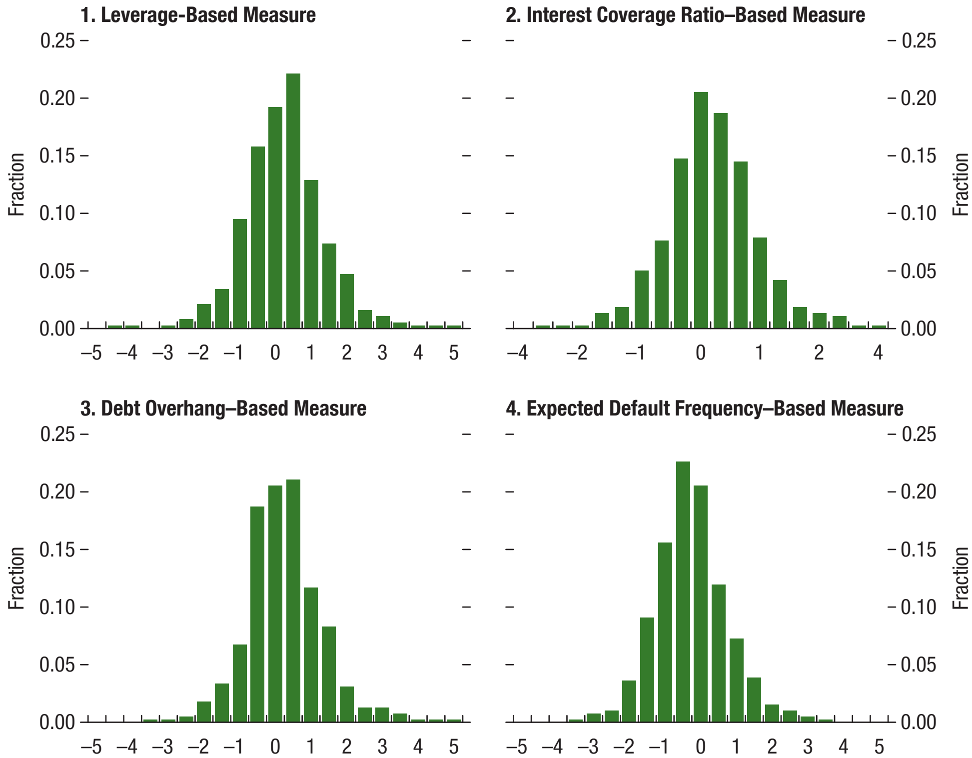
Source: IMF staff.
Note: Top (bottom) issuers are firms in the top (bottom) quintile of the distribution of the ratio of change in net debt to lagged total assets. A firm's vulnerability is measured by its decile in the distribution of a vulnerability indicator (for example, expected default frequency).

This box was prepared by Jérôme Vandenbussche.

[1]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.

Box 2.1 *(continued)*

Figure 2.1.2. Histograms of Measures of the Riskiness of Credit Allocation



Sources: Worldscope; and IMF staff estimates.
Note: The panel covers 55 economies for the period 1991–2016. Data are demeaned at the country level. The value of the riskiness of credit allocation is shown on the *x*-axis.

the country level to construct the histograms shown in the figure and in the analysis. Differences in the average value of the indicator across countries may reflect differences in the industrial composition of their corporate sectors, so these differences cannot be interpreted to mean that some countries have riskier credit allocations.[2] Their distributions have the shape of a bell curve and have a standard deviation of about one.

[2]The long-term average of the measure in each country could also be interpreted as representing the neutral allocation of credit in the absence of cyclical fluctuations.

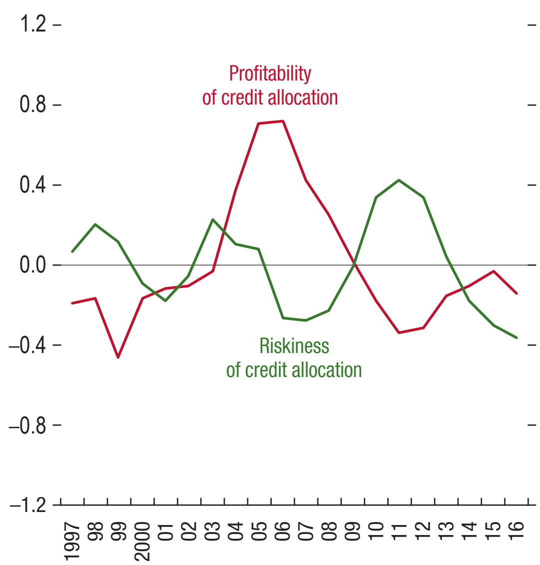
Box 2.2. Credit Allocation in China: Is Credit Flowing to the Most Profitable Firms?

Because nonfinancial corporate debt in China has continued to expand at a brisk pace, understanding how credit has been allocated may help assess the extent to which vulnerabilities are building.[1] Concerns regarding credit allocation and related medium-term macro-financial risks in China have recently focused on productivity and profitability rather than on credit risk because of the strong presence of the state in the corporate and financial sectors and the associated risk transfers to the sovereign (Song and Xiong 2018; Cong and others 2017). This box constructs a new measure of credit allocation quality that compares the profitability of firms whose credit is growing the fastest to the profitability of firms whose credit is growing the slowest—henceforth, the profitability of credit allocation—in the same way as described in Box 2.1 to evaluate these concerns.[2,3]

Although the riskiness of credit allocation has markedly declined in China since 2012, the profitability of credit allocation has experienced only a mild recovery and remained relatively low at the end of 2016 (Figure 2.2.1). The profitability of credit allocation rose significantly in the early 2000s following the reforms to state-owned enterprises (SOEs) in the 1990s, but it started declining just before the global financial crisis along with an acceleration in the credit-to-GDP ratio. This indicator continued declining during and after the global financial crisis as a large stimulus plan was put in place in 2009–10. The riskiness of credit allocation also started climbing in that period, but declined significantly after 2011–12, while the profitability of credit allocation experienced only a mild recovery and remains low by historical standards.

The decline in the profitability of credit allocation over the past decade has been stronger among SOEs and firms in traditional sectors. SOEs have drawn attention for their relatively high share of credit flows in recent years (IMF 2017a), their role as policy tools for achieving growth targets and development goals (Maliszewski and others 2016; Song and Xiong 2018), and their low relative profitability (Dollar and Wei 2007). From 2007 to 2011, the decline in the profitability of credit allocation took place both within the universe of SOEs and within the universe of private firms. However, while the decline has continued since then within the group of SOEs, the profitability of credit allocation has improved among private firms (Figure 2.2.2, panel 1). Furthermore, within some sectors considered to be the new engines of Chinese growth (IMF 2017b) the profitability of credit allocation has stabilized or improved over the past 10 years. This is in contrast with more traditional sectors in which a sharp fall has taken place. These sectors used to play a key role as China's drivers of economic growth and have the most severe overcapacity issues and contain a large share of distressed, or

Figure 2.2.1. China: Profitability of Credit Allocation, 1997–2016
(Index)



Sources: WIND data; and IMF staff estimates.
Note: Data are demeaned and shown as simple three-year moving averages. The riskiness of credit allocation is based on leverage data. See Annex 2.1 for definition of the variables.

This box was prepared by Qianying Chen and Peichu Xie, with assistance from Juno Xinze Yao.

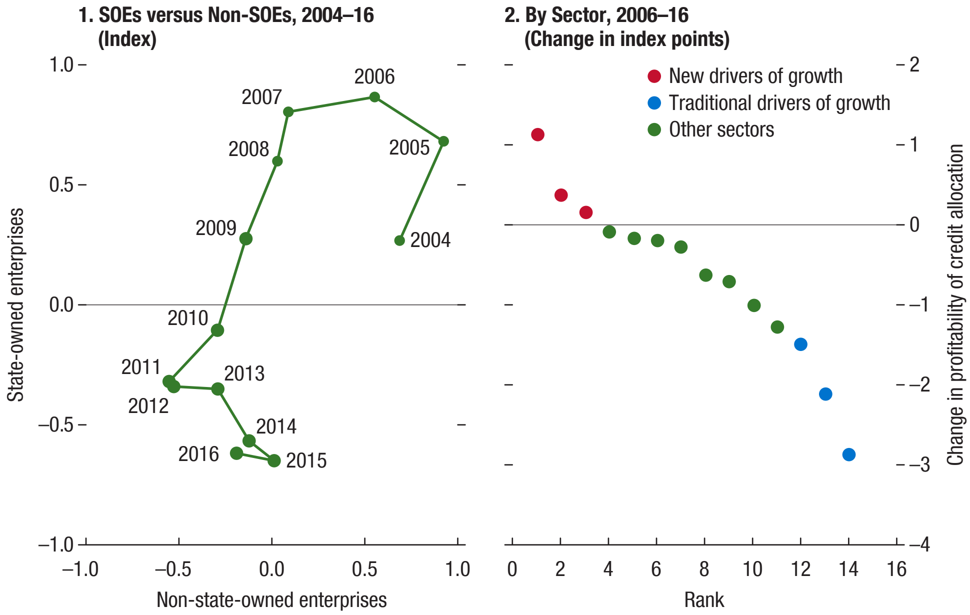
[1]For concerns about the expansion of credit in China, see IMF (2017a, 2017b). The outstanding stock of corporate debt in China reached about 163 percent of GDP at the end of 2017.

[2]The credit risk dimension of the quality of credit allocation in China may also have more implications for medium-term growth and the fiscal sector than for short-term financial stability (Song and Xiong 2018). The literature is typically focused on the share of credit to firms with public ownership or with relatively poor fundamentals in total credit (Lam and others 2017).

[3]See Annex 2.1 for details on data sources.

Box 2.2 *(continued)*

Figure 2.2.2. China: Profitability of Credit Allocation, by Ownership and Sector



Sources: WIND data; and IMF staff estimates.
Note: Data are demeaned and shown as a simple three-year moving average. "New drivers" refer to sectors identified as the new drivers of growth (IMF 2017a). These sectors are information and communication technology (ICT), technology hardware and equipment, health care equipment and services, pharmaceuticals, biotechnology, and life sciences. Traditional drivers are automobiles and components, energy, and materials. Other sectors are transportation, retail, capital goods, media, software and services, consumer goods and services, real estate, and utilities. The simple three-year moving average of the indicator is used to compute the change between 2006 and 2016. To have at least 40 firms for each industry in 2006, the one-year moving average is used for the ICT sector, and the two-year moving average is used for the energy, media, and software and services sectors. See Annex 2.1 for variable definitions. SOEs = state-owned enterprises.

"zombie" firms (Lam and others 2017). The quality of credit allocation within other industries has also declined since 2006, but to a much lesser extent (Figure 2.2.2, panel 2). These findings complement and are consistent with those of Lam and others (2017) and call for a sectoral approach to the analysis of financial vulnerabilities and associated medium-term financial stability risks in China.

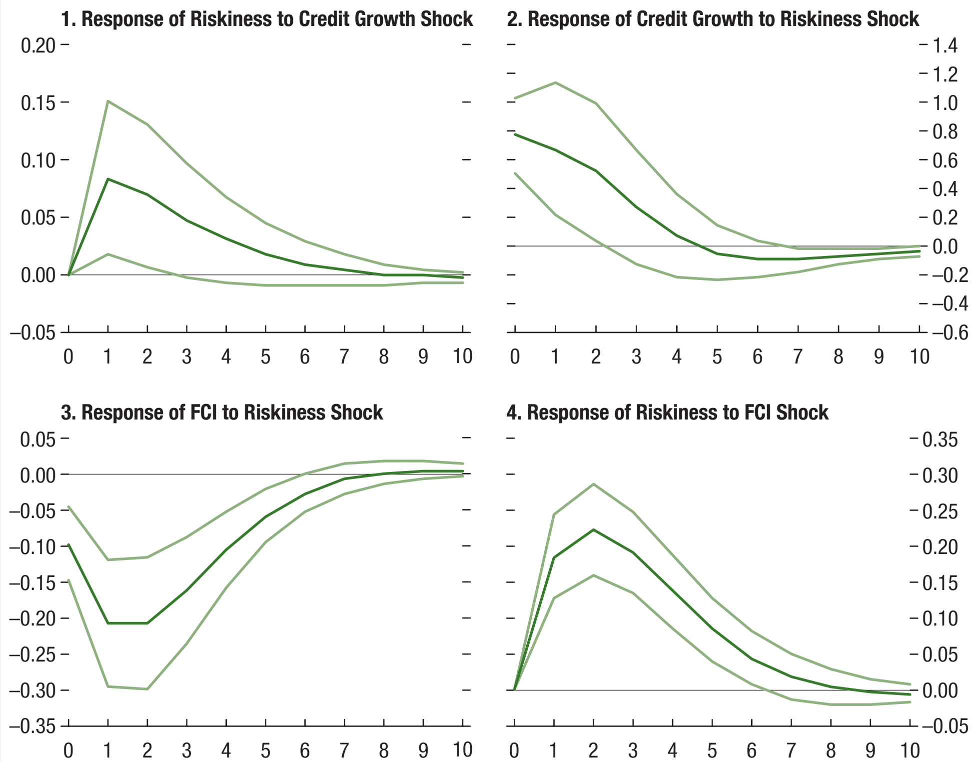
Box 2.3. The Joint Dynamics of the Riskiness of Credit Allocation, Financial Conditions, Credit Expansions, and GDP Growth

This box analyzes the joint dynamics of the leverage-based measure of riskiness of credit allocation, financial conditions, credit growth, and the business cycle. The results of a panel vector autoregression (VAR) using annual data for 41 countries from 1991 to 2016 suggest that loosening financial conditions leads to riskier credit allocation over a two- to three-year horizon, as well as to credit expansion and higher GDP growth (Figure 2.3.1).[1] The response of the riskiness of

This box was prepared by Luis Brandão-Marques.

[1]The panel VAR includes the financial conditions index (FCI), GDP growth, change in credit to the private sector to GDP, and the leverage-based measure of the riskiness of credit allocation, as well as country fixed effects, and uses one lag. The VAR is estimated using Abrigo and Love's (2016) generalized method of moments package for Stata (pvar), which in this case is warranted because of the relatively short time series available

Figure 2.3.1. The Riskiness of Credit Allocation and Financial Conditions



Source: IMF staff.
Note: The figure shows the responses of a given variable to an orthogonal shock to another variable. The responses are estimated using a panel vector autoregression (VAR) of the financial conditions index (FCI), GDP growth, credit growth, and the leverage-based measure of riskiness of credit allocation, using yearly data (1991–2016) for 41 countries. The VAR includes country fixed effects and one lag. The responses of the FCI (panel 3) and the riskiness of credit allocation (panels 1 and 4) are in standard deviations. The responses of credit growth (panel 2) are in percent of GDP. A rise in the FCI means a loosening of financial conditions. The *x*-axis in all panels is years after the shock. The dark-green lines are the average response, and the light-green lines are confidence bands at the 90 percent level.

Box 2.3 *(continued)*

credit allocation to shocks to credit and GDP growth are like those documented in the chapter and corroborate the chapter's findings about the cyclicality of this measure. Importantly, an increase in the riskiness of credit allocation is followed by a tightening (decline) in financial conditions. The results of the panel VAR also show that credit growth increases significantly after an increase in the riskiness of credit allocation. This response is likely caused by an unobserved loosening of credit standards that also leads to a more immediate deterioration in credit quality.[2] Results from a similar panel VAR augmented to include lending standards (not shown), albeit with a much smaller sample size, seem to support this hypothesis.[3]

(on average, 19 years per country). The responses of each variable in the VAR to orthogonal shocks to the variables are measured using a simple Cholesky decomposition. The ordering is such that the riskiness of credit allocation comes first, followed by credit growth and GDP growth, and the FCI is last. Although economic theory does not provide clear guidance for which variables should come first, these results assume that the FCI responds contemporaneously to all other variables. In addition, the analysis assumes that the riskiness of credit allocation does not respond contemporaneously to credit growth, GDP growth, or financial conditions; it responds only with a lag. Changing the ordering of the other variables or including more lags in the specification does not materially affect results.

[2]Looser lending standards imply that lenders increase credit to previously credit-constrained firms with low creditworthiness. Therefore, the perceived increase in the riskiness of the allocation of credit across firms is followed by higher credit growth.

[3]The panel VAR augmented with lending standards also shows that GDP first rises, but then declines after an increase in the riskiness of credit allocation. This could be consistent with the higher riskiness of credit allocation feeding the trade-off between current economic and financial conditions and future financial vulnerabilities (Adrian and Liang 2018). However, higher-frequency data are probably needed to tease out all effects.

Box 2.4. The High-Yield Share during a Credit Boom and Output Growth

This box focuses on an alternative measure of the riskiness of credit allocation, the high-yield (HY) share of bond issuance (see Kirti 2018 for details). The HY share is based solely on information from bond markets. It provides a simple, complementary approach to the main metrics used in this chapter. The HY share can be constructed for a sample of 38 countries, with coverage for some starting in 1980. Greenwood and Hanson (2013) construct the HY share for the United States and show its relevance for predicting excess bond returns; López-Salido, Stein, and Zakrajšek (2017) also show that it has macroeconomic relevance for the United States.

For the analysis in this box, the HY share is based on issuance by nonfinancial corporations and governments. It is procyclical: it rises when recent economic performance has been good and falls when recent economic performance has been bad. A procyclical HY share suggests extrapolative dynamics, consistent with the narratives of Minsky (1977, 1986) and Kindleberger (1978). The HY share also moves in line with survey measures of bank lending standards.

Focusing on a set of 25 advanced economies, this box examines whether credit booms with a rising HY share are followed by lower GDP growth in subsequent years. Credit booms are defined here as episodes in which the change in the credit-to-GDP ratio over the previous five years is high relative to recent international experience. To examine the role of the HY share, local projection specifications that interact dummies for credit booms with the average change in the HY share over the course of the boom are used.

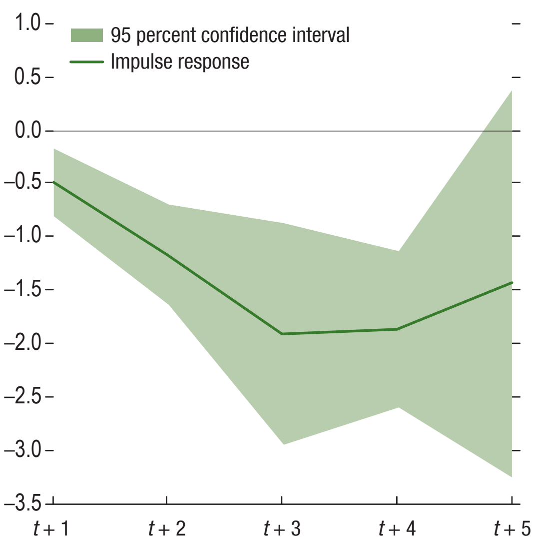
Credit booms with a rising HY share are followed by lower growth over the subsequent three to four years. Figure 2.4.1 shows the impulse response for an increase in the HY share over the course of the boom. A one standard deviation increase in the HY share during a credit boom lowers cumulative GDP growth over the next three years by 2 percentage points. The HY share also helps separate good from bad credit booms: the probability of growth being low following a credit boom is very low given a "good" HY indicator and substantially higher given a "bad" HY indicator.

These results suggest that issuance quality (using the HY share as a proxy) during a credit boom contains information about growth out to three or four years and that credit booms with a rising HY share merit special attention from policymakers.

This box was prepared by Divya Kirti.

Figure 2.4.1. Impulse Response of Cumulative Real GDP Growth to a High-Yield Share Shock Given a Credit Boom

(Percent)



Sources: Bank for International Settlements; Dealogic; IMF, World Economic Outlook database; and IMF staff calculations.
Note: The sample comprises 25 advanced economies. Time periods are shown on the *x*-axis.

Annex 2.1. Description and Definition of Variables

The core of this chapter uses firm-level data from the Worldscope database, which covers the universe of listed firms in many economies around the world. The sample is first cleaned by dropping financial sector firms (except those in the real estate sector). Second, observations are dropped if their values are incompatible with the economic content of the data; for example, 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 exceeds 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 economy-year pairs with no fewer than 40 firms and available information on aggregate credit to the private sector are kept.[33] After all cleaning, about 500,000 nonfinancial firm-year observations from 55 economies during 1991 to 2016 are left in the sample.

The Orbis database is used for the robustness analysis. It covers both listed and unlisted firms. The data are cleaned following the guidance in Kalemli-Özcan and others (2015). In addition, only observations with full information on net debt issuance, leverage, earnings before interest and taxes (EBIT), loans, and long-term debt are kept. Then, only economy-year pairs with at least 50 nonfinancial (including real estate) firms are kept. In the end, the Orbis sample covers 50 economies. Data availability in several economies is relatively poor for the 1990s, and panels are very unbalanced in most economies before 2005. A balance is struck by choosing 2000 as the start date for the Orbis-based analysis.

[33]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 have only 38 or 39 observations. For the construction of the debt overhang–based indicator, a minimum of 40 observations for non-zero debt is also required. For the construction of the expected default frequency–based indicator, a minimum of 40 observations for expected default frequency is also required.

The WIND database, which covers listed Chinese firms, is used for the analysis in Box 2.2. The advantage of using WIND over Worldscope is that it provides annual information on ownership. Observations are dropped if (1) key financial variables (net debt issuance, total assets, leverage, EBITDA, interest expenses, and market capitalization) are missing; (2) values are incompatible with the economic content of the data (such as negative values of total assets, total liabilities, market capitalization, or interest expenses); (3) values deviate from accounting identities (for example, the sum of total liability and equity book value is greater than total assets by 5 percent or more); or (4) the inception date is missing or invalid. In addition, only one observation a year is kept for firms listed on several stock markets. Only years with at least 50 nonfinancial (including real estate) firms are kept. In the end, about 37,000 firm-year pairs from 1995 to 2016 are used in the analysis. Ownership information is available for most firms only from 2004.

The leverage ratio is defined as the ratio of total debt to total assets. The interest coverage ratio (ICR) is defined as the ratio of interest expenses to EBITDA. The debt overhang measure is defined as the ratio of total debt to EBITDA. The expected default frequency (EDF) is computed using the Black-Scholes-Merton model as in Vassalou and Xing (2004). The ingredients in the model are the value of equity, the sum of short-term debt and half of long-term debt and interest payments, expected returns, the risk-free rate, and the volatility of the price of equity. The return on assets (used in Box 2.2) is defined as the ratio of EBITDA to total assets. Because availability of EBITDA is poor for some countries in the Orbis database, EBIT is used instead to compute the debt overhang indicator. Availability of data on interest expenses is also poor for several countries in Orbis, so the ICR is not used in this robustness exercise. Computing the EDF requires firm-level equity market information and therefore cannot be done for unlisted firms.

The list of economies included in the analysis is provided in Annex Table 2.1.1. Other data sources, definitions, and transformations used in this chapter's analysis are summarized in Annex Table 2.1.2.

Annex Table 2.1.1. Riskiness of Credit Allocation: Economies Included in the Analysis

	Start Year			Start Year	
	Worldscope	Orbis		Worldscope	Orbis
Advanced Economies			**Emerging Market Economies**		
Australia*	1991	2000	Argentina*	2000	n.a.
Austria*	1991	2002	Brazil*	1992	2000
Belgium*	1991	2000	Bulgaria*	2006	2000
Canada*	1991	2000	Chile*	1995	2000
Czech Republic*	1997	2000	China*	2000	2000
Denmark*	1991	2000	Croatia	2006	2000
Estonia	n.a.	2000	Egypt	2006	n.a.
Finland*	1991	2000	Hungary*	n.a.	2000
France*	1991	2000	India*	1993	2002
Germany*	1991	2000	Indonesia*	1992	2002
Greece*	1994	2000	Jordan	2006	n.a.
Hong Kong SAR	1991	2002	Kuwait	2006	2009
Iceland	n.a.	2000	Malaysia*	1991	2000
Ireland*	1999	2000	Mexico*	1995	2000
Israel*	2000	2002	Morocco	2009	n.a.
Italy*	1991	2000	Oman	2006	n.a.
Japan*	1991	2000	Pakistan	1995	2000
Korea*	1993	2000	Peru*	2001	2002
Netherlands*	1991	2000	Philippines*	1996	2002
New Zealand*	1999	n.a.	Poland*	2000	2000
Norway*	1991	n.a.	Romania	2006	2000
Portugal*	1996	2000	Russia*	2005	2000
Singapore	1991	2000	Saudi Arabia	2006	n.a.
Slovak Republic	n.a.	2000	Serbia	2010	2000
Spain*	1991	2000	South Africa*	1991	2000
Sweden*	1991	2000	Sri Lanka	2006	2006
Switzerland*	1991	2000	Thailand*	1993	2000
United Kingdom*	1991	2000	Turkey*	1997	n.a.
United States*	1991	2000	Ukraine	2008	2000
			Vietnam*	2007	2005

Source: IMF staff.
Note: End year for Worldscope is 2016; for Orbis, 2015. n.a. = data not available.
* The financial conditions index is available (see the October 2017 *Global Financial Stability Report* for the methodology).

Annex 2.2. The Determinants of the Riskiness of Credit Allocation

This annex provides a general overview of the empirical methodologies used in this chapter to analyze the cyclical determinants of the riskiness of credit allocation and its relationship to institutional and policy variables. A finding is defined as robust across measures when the regression coefficient is significant for at least two of the four measures and when the sign is identical across all four measures. Consistency of the signs of the effects in level and in interaction is also required.

The results are robust to using alternative data sources for credit, including credit data compiled by the Bank for International Settlements (both for total credit to the nonfinancial private sector and for credit to the nonfinancial corporate sector), to using different ways to capture the business cycle (output gap) and credit cycle (real credit growth), and to estimating two-way clustered standard errors at country and year levels.

Cyclicality of the Riskiness of Credit Allocation

The empirical specification is as follows:

$$Riskiness^X_{i,t} = \alpha^X_i + \gamma^X_t + \beta^X_1 \Delta\, Credit_{i,t} + \beta^X_2 \Delta GDP_{i,t} + \beta^X_3 Appreciation_{i,t} + \varepsilon^X_{i,t}, \qquad \text{(A2.2.1)}$$

in which $X \in$ {*leverage*, *interest coverage ratio*, *debt overhang*, *expected default frequency*} represents a borrower vulnerability or credit risk indicator and, correspondingly, $Riskiness^X_{i,t}$ measures the riskiness of credit allocation based on that indicator for country i at time t. $\Delta Credit$ is the change in the ratio of bank credit to the nonfinancial private sector to nominal GDP, and

Annex Table 2.1.2. Country-Level Data Sources and Transformations

Variable	Description	Source	Transformation
Macroeconomic Variables			
Real GDP	Gross domestic product, constant prices in national currency	IMF, World Economic Outlook database	
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	
Macro-Financial Variables			
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. An increase in this index implies a net tightening.	Haver Analytics; IMF staff estimates	*Z*-Score at country level
Financial Conditions Index (FCI)	For methodology and variables included in the FCI, refer to Annex 3.2 of the October 2017 *Global Financial Stability Report*. Positive values of the FCI indicate tighter-than-average financial conditions.	IMF staff estimates	*Z*-Score at country level
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.	Bloomberg Finance L.P.; Thomson Reuters Datastream	*Z*-Score at country level
Private Credit-to-GDP Ratio	The credit provided to the private sector by domestic money banks as a share of GDP	IMF, International Financial Statistics and World Economic Outlook databases	Demeaned at country level
Stock Price-to-Book Ratio	Yearly averages of price-to-book ratios	Thomson Reuters Datastream	*Z*-Score at country level
VIX	Chicago Board Options Exchange Volatility Index	Bloomberg Finance L.P.	Logarithm; demeaned across time
Financial Stress Variables			
Systemic Banking Crisis	Dummy for systemic banking crisis start	Laeven and Valencia (forthcoming)	
Banking Sector Equity Stress	Dummy variable for banking sector stress is equal to 1 when the annual excess equity return of the banking sector (relative to a zero-coupon government bond yield with short maturity) is below the country-specific mean by at least one standard deviation in any year within the time frame. Equity return is defined as the change in the logarithm of the equity price index of the banking sector (or financial sector if a banking sector price index is not available). Money market rate or interbank lending rate is substituted for government bond yield if not available.	Thomson Reuters Datastream; Bloomberg Finance L.P.; IMF, International Financial Statistics database	
Banking Sector Characteristics			
Buffers from Banking Default	The buffer of a country's banking system (capitalization and returns) relative to the volatility of returns. It is defined as (ROA+(Equity/Assets))/sd(ROA), where ROA is return on assets. sd(ROA) is the standard deviation of ROA. ROA, Equity, and Assets are country-level aggregate figures.	World Bank, Global Financial Development Database (2017)	Demeaned at country level
Policy and Institutional Variables			
Independence of Supervisory Authority from Banks	The degree to which the supervisory authority is protected by the legal system from the banking industry. Higher values indicate greater independence.	Barth, Caprio, and Levine (2013)	Country average across years
Rareness of State-Owned Enterprises (SOEs)	The negative of the scope of state-owned enterprises (SOEs), which is the pervasiveness of state ownership across 30 business sectors measured as the share of sectors in which the state controls at least one firm.	Organisation for Economic Co-operation and Development, Economy-wide Product Market Regulation Database	Country average across years
Minority Shareholder Protection Index	Minority Shareholder Rights Protection Index	Guillén and Capron (2016)	Country average across years
Net Tightening Capital Conservation Buffers	Net tightening of macroprudential instrument regarding capital conservation buffers	Alam and others (forthcoming)	Demeaned at country level
Net Tightening Ceilings and Penalties on Bank Credit Growth	Net tightening of macroprudential instrument regarding ceilings and penalties on overall bank credit growth	Alam and others (forthcoming)	Demeaned at country level
Net Tightening Minimum Leverage Ratio	Net tightening of macroprudential instrument regarding leverage ratio	Alam and others (forthcoming)	Demeaned at country level

Source: IMF staff.

Annex Table 2.2.1. Cyclicality of the Riskiness of Credit Allocation

	(1)	(2)	(3)	(4)	(5)
				Robustness	
Variables	Dependent Variable: Riskiness of Credit Allocation Based on Leverage			Sign	Significance
Change in Credit-to-GDP Ratio	0.05***	0.04***	0.06***	4	4
	(0.01)	(0.01)	(0.01)		
Real GDP Growth	0.08***	0.12***	0.05*	4	4
	(0.02)	(0.02)	(0.03)		
Appreciation against the US Dollar	–0.04***	–0.02*	–0.05***		
	(0.01)	(0.01)	(0.01)		
Country Group	All	AE	EM		
Country Cluster	Yes	Yes	Yes		
Country Fixed Effect	Yes	Yes	Yes		
Year Fixed Effect	Yes	Yes	Yes		
Observations	986	563	423		
Number of Countries	55	26	29		
R^2	0.31	0.34	0.37		

Source: IMF staff estimates.
Note: Dependent variable = riskiness of credit allocation based on leverage for columns (1)–(3). For robustness, the cyclicality of the other three measures of the riskiness of credit quality (based on interest coverage ratio, debt overhang, and expected default frequency) is investigated in the full sample. The number of measures (out of four) that have the same sign and that are significant at the 10 percent level or higher is reported in columns (4) and (5). See Annex Table 2.1.1 for countries and years in the sample. See Annex Table 2.1.2 for definitions and source of all variables. In all specifications, standard errors are clustered at the country level. Standard errors are in parentheses. AE = advanced economies; EM = emerging market economies.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

ΔGDP is real GDP growth. Domestic currency appreciation against the US dollar is included to control for a potential mechanical valuation effect on the riskiness of credit allocation from debt denominated in foreign currency. Both country (α_i^X) and year (γ_t^X) fixed effects are included. The standard errors are clustered at the country level for all specifications.

Results are provided in Annex Table 2.2.1. The results also hold if the fiscal position is controlled for through the general government structural balance. In addition, the results are robust (and coefficients quantitatively very similar) when instrumenting GDP growth and the change in the credit-to-GDP ratio by their lagged values to account for their potential endogeneity.

Financial Conditions, Lending Standards, and the Riskiness of Credit Allocation

The following equation is estimated:

$$Riskiness_{i,t}^X = \alpha_i^X + \gamma_t^X + \beta^X Controls_{i,t} + \delta^X FC_{i,t} + \theta^X \times FC_{i,t} \times \Delta Credit_{i,t} + \varepsilon_{i,t}^X, \quad \text{(A2.2.2)}$$

in which $Controls_{i,t}$ is a vector of control variables including change in the credit-to-GDP ratio, real GDP growth, and domestic currency appreciation as discussed in the previous section. The standard errors are clustered at the country level, as before. The term $FC_{i,t}$ represents a financial conditions index (FCI), financial variables representing specific components of the broad index, or a measure of lending standards. Both $\Delta Credit$ and FC are demeaned at the country level. The estimated coefficient $\hat{\delta}^X$ measures the level effect of $FC_{i,t}$ on the riskiness of credit allocation when demeaned $\Delta Credit$ is 0. The estimated coefficient $\hat{\theta}^X$ captures the marginal effect on the credit cyclicality of the riskiness of credit allocation caused by a change in the FCI, financial variables, or lending standards.

The results for lending standards, FCI, corporate spreads, stock market price-to-book ratio, and log VIX (Chicago Board Options Exchange Volatility Index) are shown in Annex Table 2.2.2. Columns (1)–(5) show the results obtained when each financial variable enters the regression individually. The impact of other financial variables, such as stock market volatility, a credit boom dummy (as defined in Dell'Ariccia and others 2016), length of credit boom, a dummy to capture different phases of a credit boom, cross-border bank-flows-to-GDP ratio, and housing price inflation is also investigated. However, none of these variables has a robust significant impact on the riskiness of credit allocation, so they are not included in the table.

Annex Table 2.2.2. Impact of Financial Conditions and Lending Standards on the Riskiness of Credit Allocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						Robustness	
Variables	Dependent Variable: Riskiness of Credit Allocation Based on Leverage					Sign	Significance
Change in Credit-to-GDP Ratio	0.05***	0.05***	0.05***	0.05***	0.05***		
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)		
Bank Lending Standards	–0.10					4	1
	(0.07)						
Change in Credit-to-GDP Ratio × Bank Lending Standards	–0.03*					4	4
	(0.02)						
Financial Conditions Index (FCI)		–0.05				3	0
		(0.07)					
Change in Credit-to-GDP Ratio × FCI		–0.01**				4	4
		(0.00)					
Corporate Credit Spreads			–0.07			4	0
			(0.06)				
Change in Credit-to-GDP Ratio × Corporate Credit Spreads			–0.02**			4	2
			(0.01)				
Stock Price-to-Book Ratio				0.20***		4	4
				(0.06)			
Change in Credit-to-GDP Ratio × Stock Price-to-Book Ratio				0.01		4	0
				(0.01)			
Change in Credit-to-GDP Ratio × Log (VIX)					–0.04**	4	3
					(0.02)		
Controls	Yes	Yes	Yes	Yes	Yes		
Country Cluster	Yes	Yes	Yes	Yes	Yes		
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes		
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes		
Observations	266	824	663	949	986		
Number of Countries	21	41	37	51	55		
R^2	0.39	0.34	0.33	0.33	0.31		

Source: IMF staff estimates.
Note: Real GDP growth and domestic currency appreciation against the US dollar are controlled for in all regressions. Increase in bank lending standards means stricter bank lending standards. Increase in financial conditions index means tighter financial conditions. Dependent variable = riskiness of credit allocation based on leverage for columns (1)–(5). For robustness, the cyclicality of the other three measures of the riskiness of credit allocation (based on interest coverage ratio, debt overhang, and expected default frequency) is investigated in the full sample. The number of measures (out of four) that have the same sign and that are significant at the 10 percent level or higher is reported in columns (6) and (7). See Annex Table 2.1.1 for countries and years in the sample. See Annex Table 2.1.2 for definitions and source of all variables. In all specifications, standard errors are clustered at the country level. Standard errors are in parentheses. VIX = Chicago Board Options Exchange Volatility Index.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Policy and Institutional Settings and the Riskiness of Credit Allocation

This analysis investigates the role played by financial market depth, banking system soundness, macroprudential policy, selected aspects of the legal and institutional framework, and banking supervision quality on the riskiness of credit allocation. The following equation is estimated:

$$Riskiness^X_{i,t} = \alpha^X_i + \gamma^X_t + \beta^X Controls_{i,t} + \rho^X Z_{i,t} + \varphi^X \times Z_{i,t} \times \Delta Credit_{i,t} + \varepsilon^X_{i,t}, \quad \text{(A2.2.3)}$$

in which $Controls_{i,t}$ is the same set of control variables as in the previous section. The standard errors are clustered at the country level. The term $Z_{i,t}$ represents different measures of financial market depth, banking system soundness, macroprudential policy, the legal and institutional framework, and banking supervision quality. All financial development and financial soundness variables enter the regression in the form of a one-year lag to eliminate potential endogeneity concerns. The estimated coefficient $\hat{\rho}^X$ measures the level effect of $Z_{i,t}$ on the riskiness of credit allocation when demeaned $\Delta Credit$ is 0. The estimated coefficient $\hat{\varphi}^X$ captures the marginal effect on the credit cyclicality of the riskiness of credit allocation with respect to a change in each of the $Z_{i,t}$ variables. Because of lack of sufficient time series variation, data

Annex Table 2.2.3. Impact of Policy and Institutional Settings on the Riskiness of Credit Allocation

	Dependent Variable: Riskiness of Credit Allocation Based on Leverage									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	Financial Soundness	Macroprudential Policy				Supervision Quality	Legal and Institution Aspects		Robustness: Sign	Robustness: Significance
Change in Credit-to-GDP Ratio	0.05***	0.05***	0.05***	0.05***	0.05***	0.12***	–0.00	0.15***		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)		
Lag Buffers from Banking Default	0.01								3	0
	(0.01)									
Change in Credit-to-GDP Ratio × Lag Buffers from Banking Default	0.005**								3	2
	(0.002)									
Net Tightening of Capital Conservation Buffers		–0.45**							4	3
		(0.21)								
Change in Credit-to-GDP Ratio × Net Tightening of Capital Conservation Buffers		–0.09***							4	1
		(0.03)								
Net Tightening of Minimum Leverage Ratio			–0.29		–0.30				4	0
			(0.20)		(0.20)					
Change in Credit-to-GDP Ratio × Net Tightening of Minimum Leverage Ratio			–0.09*		–0.09*				4	2
			(0.05)		(0.05)					
Net Tightening on Ceilings and Penalties on Bank Credit Growth				–0.57	–0.57				4	2
				(0.54)	(0.54)					
Change in Credit-to-GDP Ratio × Net Tightening on Ceilings and Penalties on Bank Credit Growth				–0.07**	–0.07**				4	4
				(0.03)	(0.03)					
Change in Credit-to-GDP Ratio × Independence of Supervisory Authority from Bank						–0.09***			4	3
						(0.02)				
Change in Credit-to-GDP Ratio × Rareness of State-Owned Enterprises							–0.01*		4	4
							(0.01)			
Change in Credit-to-GDP Ratio × Minority Shareholder Protection Index								–0.02***	4	3
								(0.01)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	861	976	976	976	976	929	739	898		
Number of Countries	55	54	54	54	54	52	37	46		
R^2	0.33	0.31	0.31	0.31	0.32	0.32	0.34	0.34		

Source: IMF staff estimates.
Note: Dependent variable = riskiness of credit allocation based on leverage. Real GDP growth and domestic currency appreciation vis-à-vis the US dollar are controlled for in all regressions. Column (4) is a horse race between different macroprudential policies. The number of measures (out of four) that have the same sign and that are significant at the 10 percent level or higher is reported in columns (9) and (10). For the macroprudential policies, the robustness information is based on the horse race. See Annex Table 2.1.1 for countries and years in the sample. See Annex Table 2.1.2 for definitions and sources of all variables. In all specifications, standard errors are clustered at the country level. Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

for all variables related to the legal and institutional framework and supervisory quality are averaged at the country level and enter the regression only as an interaction term.

The results are shown in Annex Table 2.2.3. Columns (1)–(3) and (5)–(7) show the results obtained when each variable found to be robustly significant enters the regression individually.[34] Column (4) presents the results of a horse race between the macroprudential measures that are significant when entering individually.

Annex 2.3. The Riskiness of Credit Allocation and Macro-Financial Outcomes

This annex discusses the empirical methodologies used to analyze how the riskiness of credit allocation affects the occurrence of systemic banking crises, banking sector stress, and downside risks to GDP growth. The results are robust to using alternative data sources for credit, including credit data compiled by the Bank for International Settlements (for both total credit to the nonfinancial private sector and credit to the nonfinancial corporate sector). The results are also robust to the inclusion of corporate spreads, median firm leverage (or median interest coverage ratio), and share of high-yield bond issuance as an additional control variable.

[34]This analysis also investigates (1) measures of financial depth, including the ratios of private credit to GDP, bank assets to GDP, bank credit to deposits, and external loans and deposits to domestic deposits; and capital account openness; (2) other measures of banking sector soundness, including bank concentration; probability of default of the banking sector; and the ratios of bank capital to total assets, bank regulatory capital to risk-weighted assets, and bank return on equity; (3) an additional 11 types of macroprudential instruments, including countercyclical capital buffers and minimum capital requirements; (4) other measures of supervisory quality, such as a dummy for high supervisory quality based on Basel Core Principles assessments, restructuring power of the supervisory authority, and the degree of independence of the supervisory authority from political influence; and (5) other legal and institutional indicators, such as anti-self-dealing (Djankov and others 2008), burden of proof and disclosure index (La Porta, Lopez-de-Silanes, and Shleifer 2006), corruption index (La Porta, Lopez-de-Silanes, and Shleifer 2006), and the corporate governance opacity index (Brandão-Marques, Gelos, and Melgar 2013). None of these are found to have a robust significant impact on the riskiness of credit allocation.

The Impact of the Riskiness of Credit Allocation on Systemic Banking Crisis Risk

The logarithm of the odds ratio of the start of a systemic banking crisis is analyzed using the following panel logit model:

$$log\frac{P\left[Crisisstart_t = 1 \middle| X_{i,t-1}\right]}{P\left[Crisisstart_t = 0 \middle| X_{i,t-1}\right]} = \alpha_i + \beta\,\Delta Credit^{mv3}_{i,t-1} + \gamma Riskiness^{mv3}_{i,t-1} + \delta\, Controls^{mv3}_{i,t-1} + u_{i,t}, \quad \text{(A2.3.1)}$$

in which *Crisisstart* is a dummy variable equal to 1 at the start of a systemic banking crisis, as defined in Laeven and Valencia (forthcoming) and equal to 0 otherwise. *X* refers to the vector of explanatory variables. α_i is a country fixed effect. Δ*Credit* is the change in the ratio of bank credit to the nonfinancial private sector to nominal GDP.[35] *Riskiness* is the riskiness of credit allocation, based on the leverage indicator, the interest coverage ratio indicator, the debt overhang indicator, or the expected default frequency indicator. *Controls* include controls for the macroeconomic and financial environment; that is, the change in the current-account-balance-to-GDP ratio, real GDP growth, and a financial conditions index. All explanatory variables enter the equation as the lag of their simple three-year moving average and are demeaned at the country level. The selection of macroeconomic variables follows the specification of Jordà, Schularick, and Taylor (2016a).[36] An extended version of this exercise includes interaction terms between the change in the credit-to-GDP ratio and the riskiness of credit allocation. The results, presented in Annex Table 2.3.1, are robust to using alternative estimators for the panel logit model (including two-way-clustered standard errors of the coefficients).

The Effect of the Riskiness of Credit Allocation on Banking Sector Equity Stress Risk

The importance of the riskiness of credit allocation for financial stability is explored in a further dimen-

[35]The change in the credit-to-GDP ratio is winsorized at the 1 percent level to reduce the influence of outliers.

[36]This specification 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.

Annex Table 2.3.1. Panel Logit Analysis: Probability of the Occurrence of a Systemic Banking Crisis

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Dependent Variable: Start of a Systemic Banking Crisis**					
Change in Credit-to-GDP Ratio	0.202***	0.141*	0.0565	0.0745	0.0808	–0.0902
	(0.0699)	(0.0737)	(0.0849)	(0.100)	(0.108)	(0.131)
Financial Conditions Index		–1.742**	–2.536***	–2.686***	–2.907***	–4.441***
		(0.682)	(0.611)	(0.604)	(0.724)	(0.854)
Riskiness_Leverage			1.924***			
			(0.674)			
Riskiness_Interest Coverage Ratio				2.533***		
				(0.861)		
Riskiness_Debt Overhang					2.087***	
					(0.461)	
Riskiness_Expected Default Frequency						2.113***
						(0.734)
Observations	443	443	443	443	431	361
Number of Countries	21	21	21	21	20	17
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.243	0.353	0.465	0.487	0.515	0.606

Source: IMF staff estimates.
Note: 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 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.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

sion: the risk of a banking sector equity price stress event. This risk is examined using the following framework, as in Baron and Xiong (2017):

$$log\frac{P\left[stress_{t,t+h} = 1 \middle| X_{i,t-1}\right]}{P\left[stress_{t,t+h} = 0 \middle| X_{i,t-1}\right]} = \alpha_i + \beta \Delta Credit^{mv3}_{i,t-1} + \gamma Riskiness^{mv3}_{i,t-1} + \delta\, Controls^{mv3}_{i,t-1} + u_{i,t+h}, \quad \text{(A2.3.2)}$$

in which *stress* is a dummy variable equal to 1, if there is a stress event of banking sector equity prices in the time window from t to $t + h$, $h = 0,\ldots,3$. A stress event is defined as an episode in which the annual excess equity return on the banking sector (relative to a zero-coupon government bond yield of short maturity) is below the country-specific mean by more than one standard deviation. The other variables are defined in the same way as in the crisis model described previously. Controls include a financial conditions index. An extended version of this exercise includes interaction terms between the change in the credit-to-GDP ratio and the riskiness of credit allocation. Annex Table 2.3.2 presents the results. The results are robust to using alternative estimators for the panel logit model (including two-way-clustered standard errors of the coefficients).

The Impact of the Riskiness of Credit Allocation on Downside Risks to GDP Growth

The following equation is estimated:

$$\Delta y_{i,t,t+h} = \beta \Delta Credit^{mv3}_{i,t-1} + \gamma Riskiness^{mv3}_{i,t-1} + \delta \Delta Credit^{mv3}_{i,t-1} \times Riskiness^{mv3}_{i,t-1} + \rho Controls^{mv3}_{i,t-1} + u_{i,t}, \quad \text{(A2.3.3)}$$

in which $\Delta y_{i,t,t+h}$ is the cumulative real GDP growth rate over the future h years (from t to $t + h$), in which $h = 1,\ldots,3$. Riskiness and the change in the credit-to-GDP ratio are defined as in the previously described analyses. Controls include real GDP growth and a financial conditions index. The financial conditions index includes the sovereign spread, which partially captures the impact of fiscal policies.[37] All explanatory variables enter the equation as the lag of their simple three-year moving average and are demeaned at the country level. The model is esti-

[37]Fiscal policies are found to affect economic recoveries in a different empirical framework by IMF (2016).

Annex Table 2.3.2. Panel Logit Analysis: Banking Sector Equity Stress Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Dependent Variable: Bank Equity Crash between *t* and *t* + *h* (*h* = 1,3)**							
	$t+1$	$t+3$	$t+1$	$t+3$	$t+1$	$t+3$	$t+1$	$t+3$
Change in Credit-to-GDP Ratio	–0.000975	0.0129	0.0294	0.0306	0.0316	0.0317	0.0345	0.0253
	(0.0381)	(0.0433)	(0.0309)	(0.0357)	(0.0365)	(0.0427)	(0.0437)	(0.0464)
Riskiness_Leverage	0.898***	0.727***						
	(0.246)	(0.246)						
Riskiness_Interest Coverage Ratio			0.690***	0.717**				
			(0.256)	(0.320)				
Riskiness_Debt Overhang					0.569**	0.440		
					(0.223)	(0.271)		
Riskiness_Expected Default Frequency							0.451*	0.321
							(0.274)	(0.296)
Observations	573	573	573	573	552	552	505	505
Number of Countries	36	36	36	36	34	34	33	33
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0882	0.130	0.0495	0.115	0.0517	0.102	0.0388	0.0950

Source: IMF staff estimates.
Note: 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 credit-to-GDP ratio is winsorized at 1 percent. Each estimation controls for financial conditions.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

mated using quantile regressions with nonadditive fixed effects to examine the relationship between the riskiness of credit allocation and the 20th and 50th percentiles of the future growth distribution. Regressions with and without the interaction between the change in the credit-to-GDP ratio and riskiness are both estimated. The results are shown in Annex Table 2.3.3. Similar results are obtained for the leverage-based measure using Orbis data. The impact of the riskiness of credit allocation on growth is also examined using a logit regression with a low-growth outturn dummy as the dependent variable. In that exercise, low-growth outturn is equal to 1 when the cumulative real GDP growth rate over the future *h* years (from *t* to *t* + *h*) is below the 20th percentile of its country-specific distribution and equal to zero otherwise. The findings confirm those obtained in the quantile regression framework.

Annex Table 2.3.3. Impact of the Riskiness of Credit Allocation on Downside Risks to Growth *(20th and 50th percentiles of growth distribution)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Variables	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**	**20 pt**	**50 pt**
	Cumulative Real GDP Growth Rate over Future Three Years (t, $t+3$)															
Change in Credit-to-GDP Ratio	–0.232***	–0.268***	–0.239***	–0.254***	–0.228***	–0.291***	–0.172***	–0.231***	–0.224***	–0.268***	–0.192***	–0.207***	–0.219***	–0.272***	–0.213***	–0.128***
	(0.0335)	(0.0358)	(0.0364)	(0.0471)	(0.0278)	(0.0260)	(0.0274)	(0.0380)	(0.0349)	(0.0367)	(0.0233)	(0.0472)	(0.0294)	(0.0315)	(0.0369)	(0.0328)
Riskiness_Leverage	–0.468***	–0.480***	–0.494***	–0.444***												
	(0.144)	(0.107)	(0.159)	(0.127)												
Change in Credit-to-GDP Ratio × Riskiness_ Leverage			–0.0549**	–0.0820***												
			(0.0253)	(0.0288)												
Riskiness_Interest Coverage Ratio (ICR)					–0.927***	–0.421***	–1.306***	–0.391***								
					(0.207)	(0.118)	(0.237)	(0.0948)								
Change in Credit-to-GDP Ratio × Riskiness_ICR							–0.237***	–0.217***								
							(0.0467)	(0.0360)								
Riskiness_Debt Overhang									–0.406*	–0.328**	–0.522***	–0.229*				
									(0.237)	(0.140)	(0.161)	(0.132)				
Change in Credit-to-GDP Ratio × Riskiness_Debt Overhang											–0.146***	–0.204***				
											(0.0297)	(0.0277)				
Riskiness_ Expected Default Frequency													–0.879***	–0.383**	–0.942***	–0.397**
													(0.243)	(0.161)	(0.233)	(0.190)
Change in Credit-to-GDP Ratio × Riskiness_ Expected Default Frequency															–0.0798	–0.171***
															(0.0749)	(0.0199)
Observations	602	602	602	602	602	602	602	602	592	592	592	592	532	532	532	532
Number of Countries	41	41	41	41	41	41	41	41	41	41	41	41	39	39	39	39

Source: IMF staff estimates.
Note: Standard errors are in parentheses. Explanatory variables enter the regressions 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 real GDP growth and a financial conditions index. pt = percentile.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

References

Abrigo, Michael R. M., and Inessa Love. 2016. "Estimation of Panel Vector Autoregression in Stata." *Stata Journal* 16 (3): 778–804.

Acharya, Viral V., Tim Eisert, Christian Eufinger, and Christian W. Hirsch. 2016. "Whatever It Takes: The Real Effects of Unconventional Monetary Policy." SAFE Working Paper 152, Research Center SAFE—Sustainable Architecture for Finance in Europe, Goethe University, Frankfurt.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2016. "Vulnerable Growth." Federal Reserve Bank of New York Staff Report 794, New York.

Adrian, Tobias, Daniel Covitz, and Nellie Liang. 2015. "Financial Stability Monitoring." *Annual Review of Financial Economics* 7 (1): 357–95.

Adrian, Tobias, and Nellie Liang. 2018. "Monetary Policy, Financial Conditions, and Financial Stability." *International Journal of Central Banking* 14 (1): 73–131.

Adrian, Tobias, and Hyun Song Shin. 2014. "Procyclical Leverage and Value-at-Risk." *Review of Financial Studies* 27 (2): 373–403.

Alam, Zohair, Adrian Alter, Jesse Eiseman, Gaston Gelos, Hee-don Kang, Machiko Narita, Erlend Nier, and Naixi Wang. Forthcoming. "Digging Deeper—Evidence on the Effects of Macroprudential Policies from a New Database." IMF Working Paper, International Monetary Fund, Washington, DC.

Altman, Edward I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *Journal of Finance* 23 (4): 189–209.

———. 2013. "Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA Models." In *Handbook of Research Methods and Applications in Empirical Finance*, edited by Adrian R. Bell, Chris Brooks, and Marcel Prokopczuk, 428–56. Cheltenham, UK: Edward Elgar Publishing.

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.

Barth, James R., Gerard Caprio Jr., and Ross Levine. 2013. "Bank Regulation and Supervision in 180 Countries from 1999 to 2011." *Journal of Financial Economic Policy* 5 (2): 111–219.

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.

Brandão-Marques, Luis, Gaston Gelos, and Natalia Melgar. 2013. "Country Transparency and the Global Transmission of Financial Shocks." IMF Working Paper 13/156, International Monetary Fund, Washington, DC.

Caballero, Ricardo J., and Alp Simsek. 2017. "A Risk-Centric Model of Demand Recessions and Macroprudential Policy." NBER Working Paper 23614, National Bureau of Economic Research, Cambridge, MA.

Campbell, John Y., Jens Dietrich Hilscher, and Jan Szilagyi. 2011. "Predicting Financial Distress and the Performance of Distressed Stocks." *Journal of Investment Management* 9 (2): 14–34.

Cong, Lin, Haoyu Gao, Jacopo Ponticelli, and Xiaoguang Yang. 2017. "Credit Allocation under Economic Stimulus: Evidence from China." Unpublished, University of Chicago.

Damodaran, Aswath. 2014. *Applied Corporate Finance*, 4th edition. Hoboken, NJ: Wiley.

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.

Djankov, Simeon, Rafael La Porta, Florencio Lopez-de-Silanes, and Andrei Shleifer. 2008. "The Law and Economics of Self-Dealing." *Journal of Financial Economics* 88 (3): 430–65.

Dollar, David, and Shang-Jin Wei. 2007. "Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China." IMF Working Paper 07/9, International Monetary Fund, Washington, DC.

Farhi, Emmanuel, and Iván Werning. 2016. "A Theory of Macroprudential Policies in the Presence of Nominal Rigidities." *Econometrica* 84 (5): 1645–704.

Fishburn, Peter C., and R. Burr Porter. 1976. "Optimal Portfolios with One Safe and One Risky Asset: Effects of Changes in Rate of Return and Risk." *Management Science* 22 (10): 1064–73.

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

Geanakoplos, John. 2010. "The Leverage Cycle." In *NBER Macroeconomics Annual 2009*, Vol. 24, edited by Darren Acemoglu, Kenneth Rogoff, and Michael Woodford. Cambridge, MA: National Bureau of Economic Research.

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.

Guillén, Mauro F., and Laurence Capron. 2016. "State Capacity, Minority Shareholder Protections, and Stock Market Development." *Administrative Science Quarterly* 61 (1): 125–60.

Holmstrom, Bengt, and Jean Tirole. 1997. "Financial Intermediation, Loanable Funds, and the Real Sector." *Quarterly Journal of Economics* 112 (3): 663–91.

International Monetary Fund (IMF). 2016. "Debt: Use It Wisely." *Fiscal Monitor*, Washington, DC, October.

———. 2017a. "Financial Sector Stability Assessment Report, People's Republic of China." Country Report 17/280, Washington, DC.

———. 2017b. "People's Republic of China—Staff Report for the 2017 Article IV Consultation." Country Report 17/205, Washington, DC.

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.

———. 2017. "Macroprudential Policy, Countercyclical Bank Capital Buffers and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments." *Journal of Political Economy* 125 (6): 2126–77.

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.

Kalemli-Özcan, Şebnem, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas. 2015. "How to Construct Nationally Representative Firm-Level Data from the ORBIS Global Database." NBER Working Paper 21558, National Bureau of Economic Research, Cambridge, MA.

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.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2): 211–48.

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

La Porta, Rafael, Florencio Lopez-de-Silanes, and Andrei Shleifer. 2006. "What Works in Securities Laws?" *Journal of Finance* 61 (1): 1–32.

Laeven, Luc, and Fabian Valencia. Forthcoming. "Systemic Banking Crises Database." IMF Working Paper, International Monetary Fund, Washington, DC.

Lam, W. Raphael, Alfred Schipke, Yuyan Tan, and Zhibo Tan. 2017. "Resolving China's Zombies: Tackling Debt and Raising Productivity." IMF Working Paper 17/266, 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.

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.

Maliszewski, Wojciech, Serkan Arslanalp, John Caparusso, José Garrido, Si Guo, Joong Shik Kang, W. Raphael Lam, and others. 2016. "Resolving China's Corporate Debt Problem." IMF Working Paper 16/203, International Monetary Fund, Washington, DC.

Matutes, Carmen, and Xavier Vives. 2000. "Imperfect Competition, Risk Taking, and Regulation in Banking." *European Economic Review* 44 (1): 1–34.

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.

Ohlson, James A. 1980. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research* 18 (1): 109–31.

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

Schivardi, Fabiano, Enrico Sette, and Guido Tabellini. 2017. "Credit Misallocation during the European Financial Crisis." BIS Working Paper 669, Bank for International Settlements, Basel.

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.

Shumway, Tyler. 2001. "Forecasting Bankruptcy More Accurately: A Simple Hazard Model." *Journal of Business* 74 (1): 101–24.

Song, Zheng Michael, and Wei Xiong. 2018. "Risks in China's Financial System." NBER Working Paper 24230, National Bureau of Economic Research, Cambridge, MA.

Standard and Poor's. 2013. "Corporate Methodology." Standard and Poor's Rating Services, McGraw Hill Financial, New York.

Uluc, Arzu, and Tomasz Wieladek. 2017. "Capital Requirements, Risk Shifting and the Mortgage Market." ECB Working Paper 2061, European Central Bank, Frankfurt.

Vassalou, Maria, and Yuhang Xing. 2004. "Default Risk in Equity Returns." *Journal of Finance* 59 (2): 831–68.