CHAPTER 3

FINANCIAL CONDITIONS AND GROWTH AT RISK

Summary

Changes in the state of the financial system can provide powerful signals about risks to future economic activity. As in the run-up to the global financial crisis, financial vulnerabilities, understood as the extent to which the adverse impact of shocks on economic activity may be amplified by financial frictions, often increase in buoyant economic conditions when funding is widely available and risks appear subdued. Once these vulnerabilities are sufficiently elevated, they entail significant downside risks for the economy. Thus, tracking the evolution of financial conditions can provide valuable information for policymakers regarding risks to future growth and, hence, a basis for targeted preemptive action.

This chapter develops a new, macroeconomic measure of financial stability by linking financial conditions to the probability distribution of future GDP growth and applying it to a set of major advanced and emerging market economies.

The analytical approach developed in the chapter can be a significant addition to policymakers' toolkit for macro-financial surveillance. The chapter shows that changes in financial conditions shift the distribution of future GDP growth. While a widening of risk spreads, rising asset price volatility, and waning global risk appetite are significant predictors of large macroeconomic downturns in the near term, higher leverage and credit growth provide a more significant signal of increased downside risks to GDP growth over the medium term.

Thus, at the present juncture, low funding costs and financial market volatility support a sanguine view of risks to the global economy in the near term. But the increasing leverage signals potential risks down the road. A scenario of rapid decompression in spreads and an increase in financial market volatility could significantly worsen the risk outlook for global growth. These findings underscore the importance of policymakers maintaining heightened vigilance regarding risks to growth during periods of benign financial conditions that may provide a fertile breeding ground for the accumulation of financial vulnerabilities.

A retrospective, real-time analysis of the global financial crisis shows that forecasting models augmented with financial conditions would have assigned a considerably higher likelihood to the economic contraction that followed than those based on recent growth performance alone.

Improvements in predictive ability of severe economic contractions, even over short horizons, can be important for timely monetary and crisis-management policies. The ability to harness longer-horizon information from asset prices and credit aggregates can also help in the design of policy rules to address financial vulnerabilities as they develop. The richness of the results obtained across countries suggests that there is significant scope for policymakers to further adapt the approach used in this chapter to specific country conditions including, importantly, to reflect structural changes in financial markets and the real economy.

Introduction

The global financial crisis was a powerful reminder that financial vulnerabilities can increase both the duration and severity of economic recessions. Financial vulnerabilities, understood as the extent to which the adverse impact of shocks on economic activity may be amplified by financial frictions, usually grow in buoyant economic conditions when investment opportunities seem ample, funding conditions are easy, and risk appetite is high. Once these vulnerabilities are sufficiently high, they can entail significant downside risks for the economy.

This interplay between shocks, financial vulnerabilities, and growth suggests that financial indicators can provide important intelligence regarding risks to the economic outlook. Policymakers have devoted considerable attention to translating the information content of financial indicators into an assessment of financial vulnerability. Approaches that have been used include expert judgment, stress tests, and heatmaps based on multiple early-warning indicators and broad financial conditions indices. These approaches all assess financial vulnerability by linking the state of the financial system to the probability of a financial crisis or bank capital shortage.

Because policymakers care about the whole distribution of future GDP growth, linking the state of the financial system to such a distribution would enhance macro-financial surveillance. Policymakers would then be able to specify bad outcomes in terms of their risk preferences. For example, it would be possible to calculate the likelihood of output growth being below a given level and to identify thresholds for financial indicators, such as leverage, that signal heightened tail risks to growth.

This chapter develops a new analytical tool that maps financial conditions into the probability distribution of future GDP growth. In this chapter, financial conditions correspond to combinations of key domestic financial market asset returns, funding spreads, and volatility; domestic credit aggregates; and external conditions such as measures of global risk sentiment. The methodological approach extends a nascent literature that derives a direct empirical link between financial conditions and risks to the real economy and applies it to 21 major advanced and emerging market economies over the near and medium term.

The chapter examines how financial conditions provide information regarding risks to future economic growth across countries and time horizons. In advanced economies, there may be a stronger association between financial variables and future economic activity than in emerging market economies because more economic risks are traded in deeper financial markets. But, in both cases, asset prices may remain buoyant until shortly before risks materialize, as the run-up to the global financial crisis showed. Thus, incorporating information on credit aggregates such as leverage into measures of financial conditions may improve forecasts of risks to growth, especially over the medium term.

The chapter addresses the following specific questions:

- Do changes in financial conditions signal risks to future GDP growth? Are they equally informative for advanced and emerging market economies, about the intensity of recessions and the strength of booms, and over different time horizons?
- What types of financial variables are more informative regarding the risks to growth at different time horizons and in different countries?
- Could we have used financial conditions to shed light on the likelihood of extremely negative growth outcomes of the past, such as the global recession following the bankruptcy of Lehman Brothers?
- How can policymakers make use of this new tool of macro-financial surveillance?

The main findings are as follows:

- Changes in a country's financial conditions shift the distribution of future GDP growth in both advanced and emerging market economies. A tightening of financial conditions, reflected in a decompression in spreads or an increase in asset price volatility, is a significant predictor of large macroeconomic downturns within a one-year horizon. Moreover, in emerging market economies, tighter financial conditions could also portend stronger booms over the subsequent four quarters, possibly because of procyclical capital flows.

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- Asset prices are most informative about risks to growth in the short term, whereas credit aggregates provide more information over longer time horizons. A rising cost of funding and falling asset prices signal a greater threat of severe recession at time horizons of up to four quarters. Higher leverage signals increased downside risk to growth at horizons between one and three years.
- Movements in commodity prices and exchange rates affect the real economy in a significant, albeit complex, manner, making a simple economic interpretation of their predictive content challenging. On the other hand, a souring of global risk sentiment increases downside risks to growth at short time horizons of one quarter.
- In addition to these common patterns, there is heterogeneity in the information content of financial conditions for growth risks across countries. For example, while asset prices are no longer informative over horizons longer than a year for advanced economies, they remain so for emerging markets.
- A retrospective real-time analysis of the global financial crisis shows that forecasting models augmented by financial conditions would have assigned a much higher likelihood to the economic contraction that followed than those based on recent growth performance alone.

The chapter's approach to linking financial conditions and risks to growth can help policymakers in numerous ways. The findings underscore the importance of policymakers maintaining heightened vigilance regarding risks to growth during periods of benign financial conditions that may provide a fertile breeding ground for the accumulation of financial vulnerabilities. Policymakers may respond to signals of an imminent near-term dire economic outcome with crisis-management-type discretionary policy actions that encompass a range of monetary and macroprudential tools. More broadly, this also helps in the design of policy rules to address financial vulnerabilities as they develop through the introduction of appropriate countercyclical macroprudential tools. In this regard, the output of the forecasting models could be used to calibrate parameters of structural macro-financial models used to guide such policy.[1] The richness of the results obtained across countries suggests that there is significant scope for authorities to further adapt the broad approach used in this chapter to specific country conditions, including, importantly, to reflect structural changes in financial markets and the real economy.

The rest of this chapter is organized as follows. The next section discusses conceptual issues related to the links between macro-financial conditions, financial vulnerabilities, and risks to the outlook for economic growth. The subsequent section looks at how asset prices and financial aggregates combine to signal short- to medium-term risks to future GDP growth. The section after that provides an empirical assessment of the degree to which the information contained in measures of financial conditions can help forecast risks to economic growth in major advanced and emerging market economies over horizons up to one year. The final section discusses policy implications. Annexes explain the potential policy applications, construction of financial conditions, and modeling of risks to growth in more detail.

Financial Conditions and Risks to Growth: Conceptual Issues

Economic growth has a complex and nonlinear relationship with shocks and financial vulnerabilities. Theory and recent experience both support the view that financial vulnerabilities increase risks to growth.[2] When investment opportunities seem abundant and the means of financing them are easily and cheaply available, financial vulnerabilities tend to increase. Once such vulnerabilities are sufficiently high, they can amplify and prolong the impact of shocks on economic activity. GDP growth responds nonlinearly to shocks in the presence of financial vulnerabilities, which increases the likelihood of severely negative economic outcomes.[3] Under such circumstances, assessments of both the baseline growth outlook and the risks to such an outlook are informed not only by the span and severity of relevant risk factors that are the source of shocks, but also by the intelligence provided by the interplay of factors that increase financial vulnerability.

[1]Just as estimated vector autoregression models have been used to calibrate the parameters of linear dynamic general equilibrium models used to pin down optimal monetary policy rules (for example, Christiano, Eichenbaum, and Evans 2005; Del Negro and Schorfheide 2009).

[2]Empirical evidence shows that recessions accompanied by financial crises are typically much more severe and protracted than ordinary recessions (Claessens, Kose, and Terrones 2011a, 2011b).

[3]Annex 3.1 provides a framework for understanding the joint dynamics of financial vulnerabilities and growth risks in a structural macro model.

Several factors cause financial vulnerabilities to grow in a buoyant macro-financial environment. Ease of borrowing and high asset prices reduce the incentives to manage liquidity and solvency risks. Perceptions of high investment returns relative to the cost of funding and of the improved quality of collateral incentivize households and firms to increase their leverage without taking into account the potential negative externalities resulting from their collective borrowing decisions (Bianchi 2011; Korinek and Simsek 2016; Bianchi and Mendoza, forthcoming). Booming asset prices also boost the capital adequacy, lending capacity, and risk appetite of financial intermediaries (Brunnermeier and Pedersen 2009; Adrian, Moench, and Shin 2010; Adrian and Shin 2014). As intermediaries respond by increasing short-term wholesale funding to finance long-term credit exposures, maturity mismatches and other balance sheet weaknesses accumulate in the financial sector. For example, lenders' incentives to invest in costly underwriting are reduced, which can result in significant mispricing of credit risk (Gorton and Ordoñez 2014).

The need to lower significant debt and correct balance sheet mismatches can clog financial intermediation, investment, and growth for a long time once the credit cycle turns. With vulnerabilities substantially elevated, even small negative shocks can cause significant reversals because they force lenders to face up to the true quality of exposures and collateral. This results in a significant tightening in credit conditions. Some firms and households may be forced into default, while others may have to liquidate assets. The ensuing pressure on lenders' profits and collateral values can then generate further rounds of contraction in credit, investment, and growth. In addition to the direct negative impact of these events on lenders' profits, rising volatility and risk spreads constrain lenders' capacity to bear risk by increasing the capital required as a buffer against existing exposures (He and Krishnamurthy 2013; Brunnermeier and Sannikov 2014). In such circumstances, risk-bearing capacity will be affected not only by capital constraints but also by funding liquidity concerns (Gertler, Kiyotaki, and Prestipino 2017).

A large body of empirical work has examined the information content of asset prices in forecasting the *baseline* growth outlook.[4] Various asset prices have been found to be useful predictors of future output growth in some countries and in some periods. Combining forecasts obtained from models with individual asset prices appears to result in more consistent, higher-quality forecasts. Short-term yields on risk-free securities and term spreads capture the stance of monetary policy and therefore contain useful information about future economic activity (Laurent 1988; Estrella and Hardouvelis 1991; Bernanke and Blinder 1992; Estrella and Mishkin 1998; Ang, Piazzesi, and Wei 2006). Corporate bond spreads signal changes in the default-adjusted marginal return on business fixed investment (Philippon 2009) and shocks to the profitability and creditworthiness of financial intermediaries (Gilchrist and Zakrajšek 2012).[5] There is some evidence that elevated stock-return volatility can be a useful predictor of output contraction over short horizons (Campbell and others 2001), although empirical evidence for the predictive content of stock returns is weak (Campbell 1999; Stock and Watson 2003).

The key departure of this chapter is to focus on the information content of financial indicators in forecasting *risks* to growth. In addition to asset prices, credit aggregates can also be expected to provide information on the risks to growth in the short, medium, and long term. For example, a combination of low leverage and buoyant asset prices is likely to correspond, over the short term, to high expected growth (an optimistic *baseline* outlook) and a low likelihood of adverse outcomes (sanguine *risk* outlook as represented, potentially, by a probability density of short-term growth with relatively low variance). On the other hand, theory suggests that such an environment might be ideal for a buildup of vulnerabilities over the medium term, ultimately increasing the likelihood of low growth outcomes. As such a possibility becomes more certain, spreads and market volatility would rise and asset prices would fall.[6] Other financial variables can

[4]Stock and Watson (2003) produce a comprehensive survey of the literature up to the early 2000s.

[5]Gilchrist and Zakrajšek (2012) demonstrate the superiority of their constructed bond spread over alternative proxies for the default spread investigated in the earlier literature; for example, the Baa-Aaa bond spread (Bernanke 1983), the commercial paper–Treasury bill spread (Stock and Watson 1989; Friedman and Kuttner 1998), and the so-called junk bond spread (Gertler and Lown 1999).

[6]Financial indicators can be classified into two types. Fast-moving asset prices tend to signal risks to growth over the near term, whereas balance sheet aggregates change gradually over time and may indicate risks over longer horizons. The evolution of aggregates and prices is not by any means independent. For example, the growth in aggregates may, beyond a point, change market expectations of risks. This would be reflected in tightening spreads, which then signal risks to growth in the near term. For a discussion, see Adrian and Liang 2016 and Krishnamurthy and Muir 2016.

also be very informative in the context of small open advanced economies and emerging market economies. These variables include the nominal exchange rate and commodity prices, which may affect the cost of external funding and the availability of international collateral (Caballero and Krishnamurthy 2006).

This chapter refers to such a combination of financial indicators, or an index constituted of them, as financial conditions. The term "financial conditions" often refers to the ease of funding (Chapter 3 of the April 2017 *Global Financial Stability Report* [GFSR]), but here it is used to refer to the combination of a broad set of financial variables that influence economic behavior and thereby the future of the economy.[7]

This chapter examines two alternative approaches to constructing measures of financial conditions from the information contained in several financial indicators. One attractive option is a single financial conditions index (FCI). An important advantage of such a univariate FCI is the parsimony with which it aggregates the information content of multiple financial indicators. Parsimony is highly desirable for forecasting because it reduces parameter uncertainty, but it may lead to suppressing the information provided by certain variables by commingling them with other, more volatile indicators in a single index. For example, the higher variability of asset prices and risk spreads may lead them to dominate univariate FCIs, with credit aggregates being assigned small factor loadings (as is indeed the case in the application described below). Since credit aggregates may carry significant information about risks to growth at longer horizons, the chapter pursues a second approach wherein financial indicators are partitioned into three separate groups based on economic similarity. The three subindices are the *domestic price of risk* (risk spreads, asset returns, and price volatility), *credit aggregates* (leverage and credit growth), and *external conditions* (global risk sentiment, commodity prices, and exchange rates). The separation of a large set of financial indicators into these three predetermined categories is a reasonable compromise between maintaining parsimony, allowing various classes of indicators to provide separate signals about risks to growth at different horizons, and being able to provide a more direct economic interpretation of the various subindices.

[7]This notion of financial conditions is similar to the definition proposed by Hatzius and others (2010). See Annex 3.2 for details on the construction of financial conditions used in this chapter.

The chapter's empirical framework is centered on forecasts of the probability distribution of future growth outcomes based on financial conditions in a way that allows for nonlinearity and state dependence. Building on the literature on conditional density forecasting and recent research on forecasting the distribution of growth in the United States, the chapter uses financial conditions to forecast the probability distribution of future GDP growth in major advanced and emerging market economies for horizons of up to three years through quantile projections.[8] The flexibility of this approach captures the rich nonlinear interaction between shocks, financial vulnerabilities, and economic outcomes predicted by theory. For instance, consider two combinations of financial indicators that forecast the same future median growth rate. The first combination forecasts much greater downside growth risk (that is, a probability density with a significantly fatter left tail) than the second. This indicates that for a constant distribution of fundamental shocks, the economy is more likely to experience a very bad economic outcome in the future under the first configuration than under the second. In this sense, the first combination signals a financial system that is more vulnerable. These density forecasts can subsequently be exploited to construct measures of risks to economic growth associated with the state of the financial system.

Such an approach provides a natural way of assessing financial vulnerability that has several distinct advantages. First, the estimated link between financial conditions and the distribution of future economic activity would provide a close measure of financial vulnerability, understood as the extent to which the financial system amplifies shocks. Second, to the extent that policymakers care about the whole distribution of future GDP growth, it provides a complete depiction of the risks to economic activity associated with the state of the financial system. Third, it allows policymakers to define risk tolerance in terms of GDP growth, which is more general than in terms of the probability of a financial crisis as defined under specific criteria or another ad hoc metric. For instance, this approach gives precise answers to questions such as the probabil-

[8]See Annex 3.3 for details on the empirical framework. Conditional density forecasting is surveyed by Tay and Wallis (2000); Corradi and Swanson (2006); and Komunjer (2013). The chapter's methodology builds on some recent studies (Adrian, Boyarchenko, and Giannone 2016; De Nicolò and Lucchetta 2017) that establish a direct empirical link between financial conditions and risks to economic growth.

ity of GDP growth being less than –3 percent one year ahead given the current—or any hypothetical—state of the financial system.

How Do Changes in Financial Conditions Indicate Risks to Growth?

Over a horizon of one to four quarters, tighter financial conditions—as reflected in higher univariate FCIs—predict increased downside risks to GDP growth in most advanced economies and a more uncertain growth outlook in several emerging market economies. An increasing domestic price of risk signals an elevated threat of imminent, severe recession in advanced and emerging market economies. Rising leverage is a significant predictor of elevated downside risk over the medium term. Country-specific results vary considerably, suggesting a rich interplay of the drivers of growth risk.

What Underpins Economies' Financial Conditions Indices?[9]

The drivers of economies' FCIs vary considerably across a sample of major advanced and emerging market economies.[10] An increase in the FCI corresponds to tighter financial conditions, that is, higher spreads and volatility, lower asset prices, worsening risk sentiment, exchange rate depreciation, and unfavorable commodity price movements. Beyond this common finding, the relative importance of these factors in determining the evolution of FCIs varies considerably across countries. Higher corporate funding costs and worsening global risk sentiment (as captured by rising levels of the Chicago Board Options Exchange Volatility Index [VIX] and Merrill Lynch Option Volatility Estimate [MOVE] Index) tighten financial conditions across the board. But while sovereign spreads are clearly important in emerging market economies, they are rarely so in advanced economies. And while increasing commodity prices loosen financial conditions in exporters such as Australia, Brazil, Canada, Chile, and Russia, they tighten them in commodity-importing countries. Exchange rate appreciation uniformly loosens financial conditions.[11] In the case of emerging market and small open economies, this may reflect the correspondence of an appreciating exchange rate with strong capital inflows. In general, asset price shocks appear to be more important in driving changes in FCIs than credit aggregates. This pattern, however, may reflect the slower speed at which credit adjusts relative to changes in GDP at turning points in the economic cycle, especially at the end of economic booms preceding financial crises.

What Information Do Univariate FCIs Convey about Future Growth?

An increase in the FCI would signal higher downside risks in both advanced and emerging market economies. An increase in the global FCI signals heightened downside risk to world GDP growth (Figure 3.1).[12] Movements in the FCI are especially powerful signals of changes in downside tail risk to the global economy but are less informative about the baseline growth outlook and the strength of economic booms. This is reflected in the fact that the forecast of the left tail of the distribution of global GDP growth decreases significantly in response to an increase in the FCI both one quarter and four quarters ahead. In contrast, the forecasts of the central tendency of GDP growth (as captured by the median growth rate) and of the strength of booms (at the right tail of the growth distribution forecasts) are considerably less responsive to changes in the FCI, and their movement is apparent only for large changes in the FCI such as those observed in the global financial crisis. This is also the case for individual countries—the forecasts of the worst-case outcomes (at the 5th percentile of the future GDP growth distribution) are between 3 times (United States) and more than 10 times (Australia) more sensi-

[9]In this subsection, financial conditions reference the univariate FCIs described in the preceding section.

[10]The financial indicators that constitute a country's FCIs may evolve over time for many reasons, including changes in risk appetite or investor risk sentiment. The methodology used to construct the FCIs, the list of financial indicators, and the sample of countries are described in detail in Annex 3.2.

[11]Exchange rate movements may reflect a complex combination of factors. With respect to a country's FCI, changes in the exchange rate are most likely to be associated with changes in the ease of external financing conditions, which may relate either to evolving global funding conditions and risk sentiment or changes in the market's perception of the country's creditworthiness or both. Exchange rate depreciations are, in such an association, a reflection of a worsening of global conditions or in market perceptions of a country's risk profile. Empirically, such an association appears to apply to most countries covered in the chapter, although the link has been noted in the literature as relevant primarily for emerging market economies.

[12]The global FCI is defined as the first principal component of the country-level FCIs.

tive to changes in FCIs than the forecasts of the central tendency of economic growth.

Easing of global financial conditions through 2016 signaled reduced tail risk to global growth for 2017. This is evident in the upward movement in the bottom tail of the GDP growth density forecast (5th percentile) for the world economy (Figure 3.1) and a similar movement in several countries, including Australia, Brazil, South Africa, Turkey, and the United States (Figure 3.2).[13]

Nonetheless, FCIs do carry significant information regarding upside risks to future economic growth for emerging markets (Figure 3.3). In Brazil, Korea, and Mexico, higher levels of the FCI portend a more uncertain growth outlook at a one-year horizon, as reflected in coefficients of opposite signs at the lowest and highest quantiles (which imply fatter and longer tails at both ends of the distribution of future GDP growth). In some commodity-exporting countries, such as Chile, tightening FCIs appear to signal risk of stronger recessions as well as economic booms of lower intensity (Figure 3.3, panel 2).

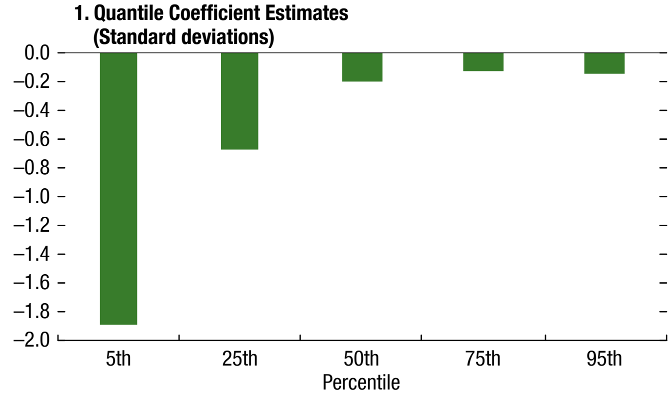
Different properties of advanced and emerging market economy business cycles may account for the differing significance of the information provided by changing FCIs across countries. Some emerging market economies and commodity exporters may have a more pronounced and symmetrical boom-bust cycle that is closely tied to export-commodity prices and global risk sentiment. Positive developments in either factor can motivate significant capital inflows, relaxing domestic financial constraints on growth.[14] When the risk environment reverses, capital flows may retrench, exchange rates can depreciate, and investment and growth can decline (Aguiar and Gopinath 2007). This may explain why a tightening of financial conditions can move the density of GDP growth to the left (Figure 3.3, panel 2). More broadly, increases in FCIs in emerging market economies may reflect domestic interest rate hikes targeted at attenuating overheating due to high domestic demand. But the higher interest rates may attract

[13]The exact magnitude of the movements can be improved by further country-specific calibration that, for instance, increases the number of financial indicators used in FCI construction, but the direction of the movements indicated by the model is quite robust and showcases the potential of this methodology.

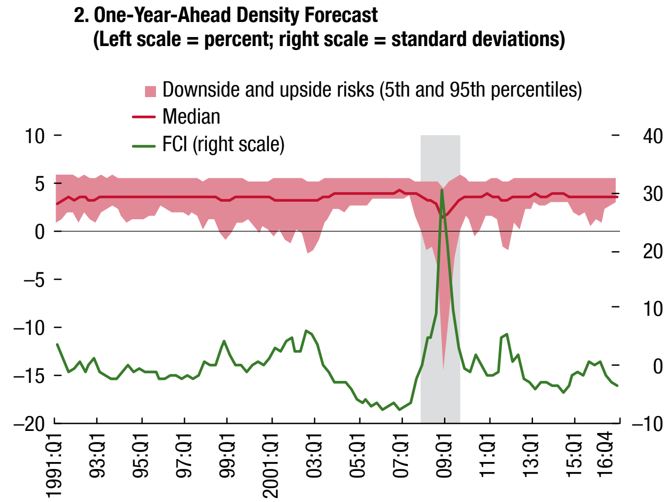
[14]For the role of commodity prices in explaining the cyclical movements of capital flows to emerging market economies, see, for example, Chapter 4 of the April 2017 *Regional Economic Outlook* for the Western Hemisphere.

Figure 3.1. Tighter Financial Conditions Forecast Greater Downside Tail Risk to Global Growth

As financial conditions tighten, the probability of a large economic contraction increases ...



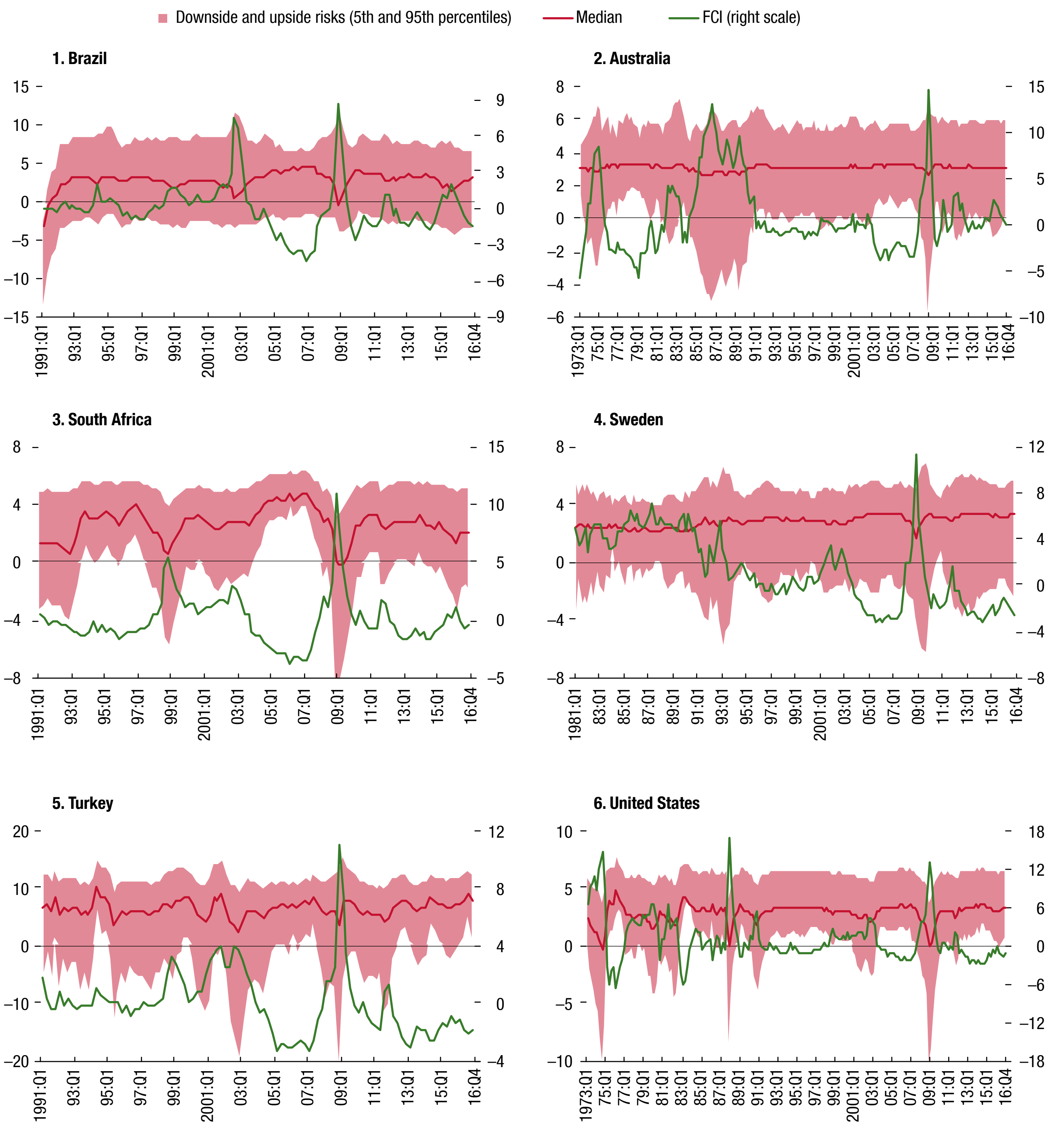
... as was seen in the recent global financial and euro area sovereign debt crises.



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: Panel 1 depicts the estimated coefficients on the current quarter FCI in a quantile regression of four-quarters-ahead GDP growth on current quarter FCI and GDP growth. Panel 2 depicts the time series of estimated, conditional 5th, 50th, and 95th quantiles of four-quarters-ahead GDP growth. The median (red) line denotes the forecast of the 50th quantile of GDP growth made four quarters earlier using the methodology described in Annex 3.3. The shaded area is bound at the top and bottom by, respectively, the forecasts of the 95th and 5th quantiles of GDP growth made four quarters earlier. FCI = financial conditions index.

Figure 3.2. Risk of Severe Recessions Is Especially Sensitive to a Tightening of Financial Conditions in Major Advanced and Emerging Market Economies

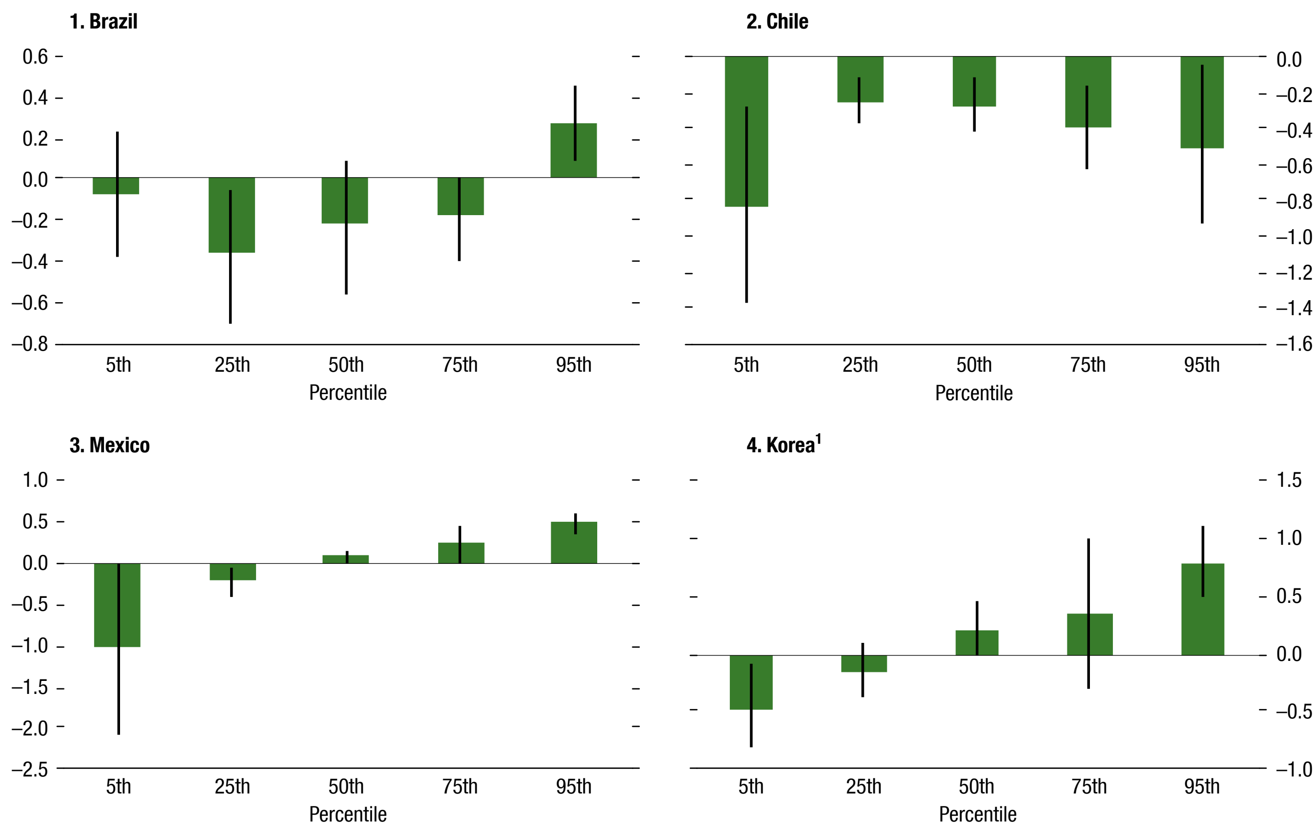
(One-year-ahead density forecasts; left scale = percent; right scale = standard deviations)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.

Note: The country-specific financial conditions indices (FCIs) are constructed using the methodology described in Annex 3.2. The median (red) line at each point in time denotes the forecast of the 50th quantile of GDP growth made four quarters earlier using the methodology described in Annex 3.3. The shaded area is bound at the top and bottom by, respectively, the forecasts of the 95th and 5th quantiles of GDP growth made four quarters earlier.

Figure 3.3. In Emerging Market Economies, Changes in Financial Conditions Also Affect Upside Risks
(Quantile regression estimates for selected emerging market economies: four quarters ahead)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The panels depict estimated coefficients on the current quarter financial conditions index (FCI) from quantile regressions of four-quarters-ahead GDP growth on current quarter FCI and GDP growth. The coefficients are standardized to depict the impact of a one standard deviation increase in current quarter FCIs on four-quarters-ahead GDP growth (also expressed in standard deviations).
[1]In line with Morgan Stanley Capital International (MSCI) markets classification criteria, Korea is classified as an emerging market economy in panel 4.

capital inflows and thereby extend ongoing credit and economic booms. This may explain why tightening of financial conditions appears to be a good indicator of growing positive and negative risks around the baseline (Figure 3.3, panels 1, 3–4).

Which Asset Prices and Aggregates Best Signal Growth Risks at Various Time Horizons?

Asset prices are differentially informative regarding the domestic price of risk across countries. Term and interbank spreads, followed by corporate and sovereign spreads, are the most important risk indicators for the investment and growth outlook across advanced economies. The dynamics of house prices are particularly important in countries where either the share of homeownership and floating-rate mortgages is high (such as the United Kingdom) or the mortgage market is a key node that underpins pricing and activity in systemic funding markets (as in the United States). The evidence for emerging market economies is more challenging to interpret for two reasons. First, data are much more limited and are available only for more recent years. Second, in many countries, financial market activity is often focused on equity and government bond markets. Unsurprisingly, therefore, analysis of available data suggests that for these countries, sovereign spreads and equity returns are most significant.

Domestic asset prices are the dominant driver of growth risks in the short term, while credit aggregates are the dominant drivers in the medium term. Results from a panel quantile regression with country fixed effects, estimated separately for advanced and emerging market economies, highlight some common patterns in the relationship between these FCI components and risks to growth.

- *Domestic price of risk:* Tightening of financial conditions caused by a rising price of risk is a significant predictor of downside growth risks over horizons of up to one year. This inverse relationship between the price of risk and the growth forecast is stronger in the left tail of the distribution of future growth and is more significant for advanced economies (Figure 3.4, panels 1–4). The price of risk becomes uninformative over longer horizons in advanced economies. In emerging market economies, an interesting pattern arises—a higher price of risk signals lower downside (tail) risks at two- to three-year horizons. One possible explanation is the negative impact of tighter domestic financial conditions on leverage and balance sheet expansion, which appears to be associated with lower risks to growth in both the short and medium term (Figure 3.4, panels 5–6).
- *Leverage:* Higher credit growth and credit to GDP signal greater downside risk to growth at horizons of one year and longer. The relationship is economically more significant at the lower quantiles of GDP growth and in advanced economies than in emerging market economies (Figure 3.5, panels 1–2). Over shorter time horizons (one quarter), however, the information content differs across countries, with rising leverage continuing to signal higher downside risks in emerging market and large advanced economies but signaling lower downside risks in small open advanced economies.
- *External conditions:* While changing external conditions convey statistically significant information regarding risks to future growth, their information content represents a complex combination of forces. For example, movements in exchange rates can reflect different risk implications through real and financial channels, each of which may be more potent at different horizons. And the impact of changes in commodity prices on risks to growth will differ depending on whether a country is a commodity exporter or importer. Consequently, the signal given by changes in external conditions proved difficult to interpret in a straightforward manner. Nonetheless, a clearer interpretation arises when isolating changes in global risk sentiment from the other external variables.[15] Higher global risk aversion, reflected in a higher VIX, signals greater downside risks to growth in the short term, including a larger threat of an imminent recession (Figure 3.6). However, increases in the VIX also signal lower downside risks to growth at longer horizons of one to two years, possibly because, in most cases, tighter global financial conditions slow the growth of leverage and balance sheet mismatches, which may lessen medium-term growth risks.

The view that emerges from these results is that the prevailing low funding costs and financial market volatility support a positive view of risks to the global economy in the short term, but increasing leverage signals potential risks down the road. In such circumstances, a scenario of a rapid decompression in spreads and increase in financial market volatility could significantly worsen the risk outlook for global growth.

How Well Do Changes in Financial Conditions Forecast Downside Risks to Growth?

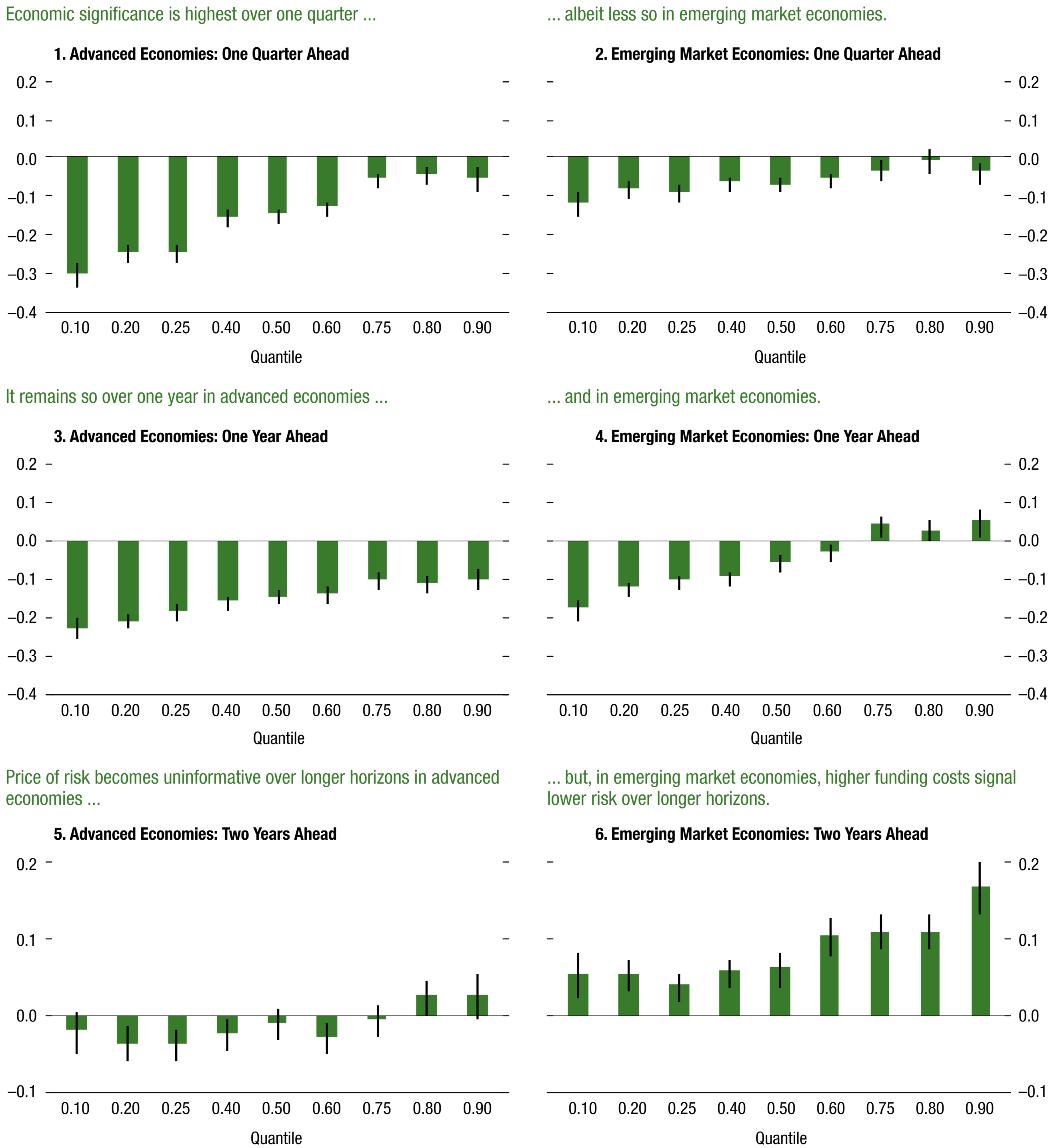
Severely adverse growth performance during the global financial crisis is used to demonstrate the potential use of measures of financial conditions in improving forecasts of risks to growth at horizons of up to one year. Augmenting growth forecast models based on past growth performance with financial conditions significantly improves forecasting ability. This is reflected in the greater likelihood that is assigned to the actual negative growth outcomes during that period.

Applying the univariate FCIs to historical episodes highlights the index's power to help predict future economic downturns over short horizons. Notably, the model was used to predict the distribution of growth for the first quarter of 2009, broadly corresponding to the peak of the global financial crisis.

- At a one-quarter horizon (that is, in the fourth quarter of 2008), conditioning the risk forecast of future growth on financial conditions (besides economic growth) adds significantly to capturing

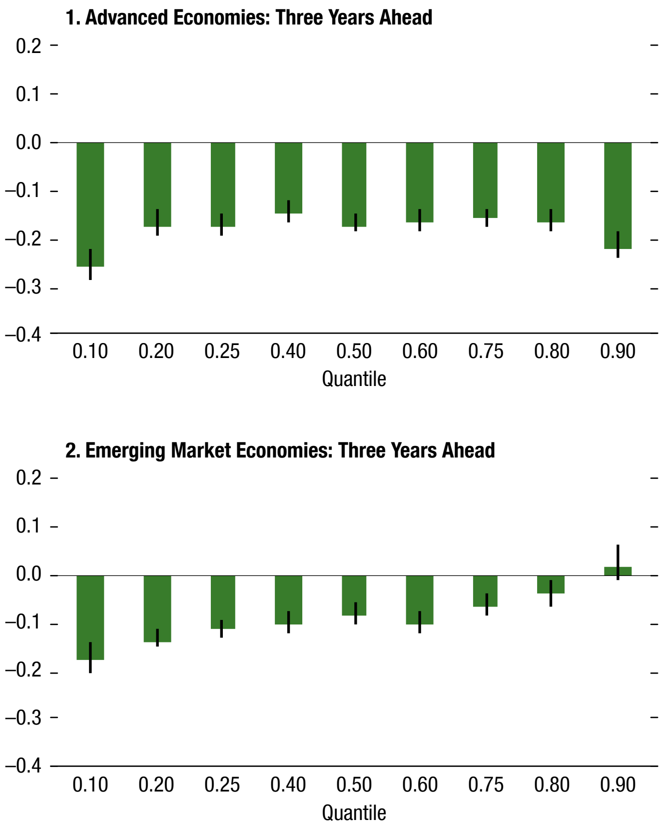
[15]Formally, a separate model of the kind described in Annex 3.2 was examined with the external conditions subindex defined as a global risk sentiment index (equal to the change in the VIX).

Figure 3.4. Higher Price of Risk Is a Significant Predictor of Downside Growth Risks within One Year
(Quantile regression coefficients)



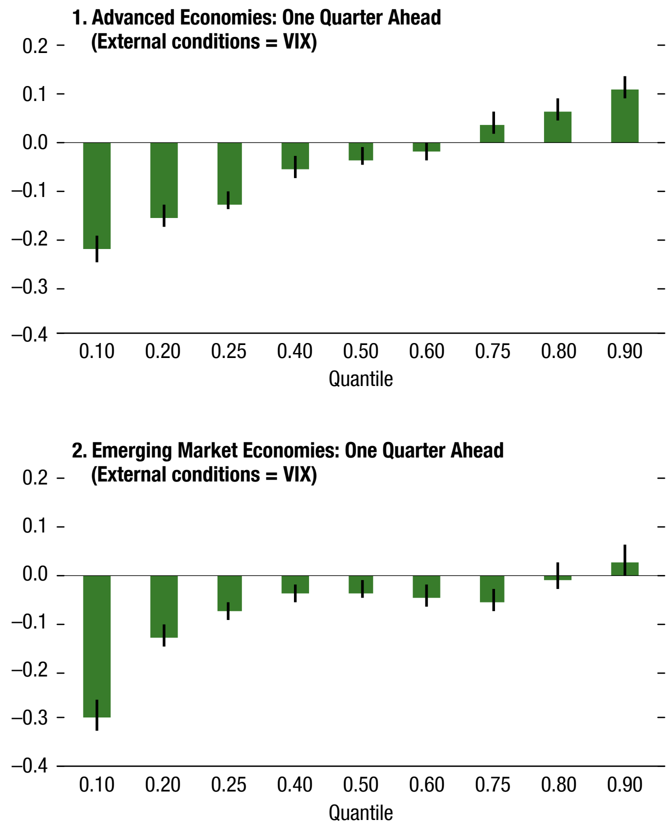
Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The panels depict coefficient estimates on the price of risk index in pooled quantile regressions of one-quarter-ahead, four-quarters-ahead, and eight-quarters-ahead GDP growth for advanced economies (left column) and emerging market economies (right column). The coefficients are standardized by centering and reducing (zero mean, unit variance) both the dependent variable and the regressors to enable comparison across quantiles, across time horizons, and between advanced and emerging market economies. The coefficient estimate for a given quantile should be read as the impact of a one standard deviation change in the price of risk on the future quantile of GDP growth also expressed in terms of standard deviations. The vertical lines in the green bars denote confidence intervals at 10 percent and, where they cross the *x*-axis, correspond to absence of statistical significance of the regressor.

Figure 3.5. Rising Leverage Signals Higher Downside Growth Risks at Longer Time Horizons
(Quantile regression coefficients)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The panels depict coefficient estimates on the credit aggregates index in pooled quantile regressions of three-years-ahead GDP growth for advanced and emerging market economies. The coefficients are standardized by centering and reducing (zero mean, unit variance) both the dependent variable and the regressors to enable comparison across quantiles, across time horizons, and between advanced and emerging market economies. The coefficient estimate for a given quantile should be read as the impact of a one standard deviation change in leverage on the future quantile of GDP growth also expressed in terms of standard deviations. The vertical lines in the green bars denote confidence intervals at 10 percent and, where they cross the *x*-axis, correspond to absence of statistical significance of the regressor.

Figure 3.6. Waning Global Risk Appetite Signals Imminent Downside Risks to Growth
(Quantile regression coefficients)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The panels depict coefficient estimates on the VIX index in pooled quantile regressions of one-quarter-ahead GDP growth for advanced and emerging market economies. The coefficients are standardized by centering and reducing (zero mean, unit variance) both the dependent variable and the regressors to enable comparison across quantiles, across time horizons, and between advanced and emerging market economies. The coefficient estimate for a given quantile should be read as the impact of a one standard deviation change in the VIX on the future quantile of GDP growth also expressed in terms of standard deviations. The vertical lines in the green bars denote confidence intervals at 10 percent and, where they cross the *x*-axis, correspond to absence of statistical significance of the regressor. VIX = Chicago Board Options Exchange Volatility Index.

imminent tail risks to growth, both at the epicenter of the crisis (that is, the United States) and in a commodity-exporting emerging market economy (Chile). Notably, the likelihood attached to poor growth outcomes around the actual realization is significantly higher if rapidly tightening financial conditions are incorporated into the growth forecast (the density in red) as opposed to a model whose only information for forecasting is the growth outcome (the density in blue) in the fourth quarter of 2008 (Figure 3.7).[16]

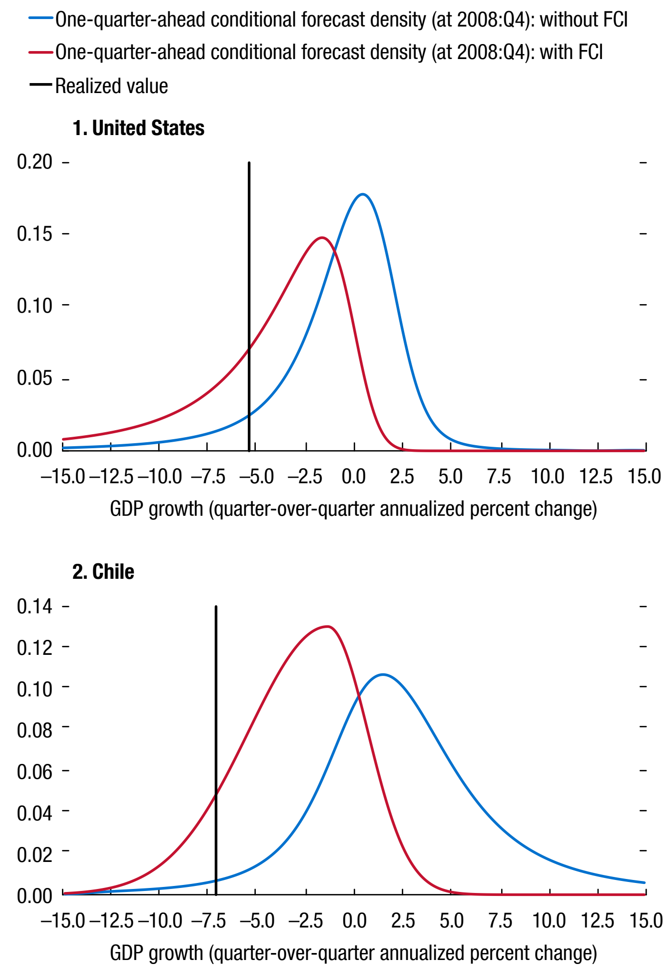
[16]GDP growth exhibits a high degree of persistence in the sample of advanced and emerging market economies covered by this chapter's analysis. Consequently, from a forecasting perspective, a quantile autoregression model of GDP growth represents a conservative and hard-to-beat benchmark against which to assess the marginal conditioning information content of financial conditions. The quantile autoregression model is unlikely to forecast rare (severe) recessions

- These results remain robust in a broader cross section of countries. Among countries that experienced a significant growth downturn during the crisis, adding FCIs to an autoregressive growth forecasting model significantly increases the conditional likelihood of a GDP growth outcome less than or equal to the actual growth outturn one quarter ahead (Table 3.1).[17] In addition to predicting a fatter left tail for the growth distribution, the average growth forecasts including FCIs are closer to the actual severe economic contraction experienced by these countries in the first quarter of 2009, and well below the market consensus, which remained relatively optimistic even after the collapse of Lehman Brothers (Table 3.2).

The exercise also shows that conditioning on univariate FCIs may not work as well at longer horizons. This possibility is evident when comparing the relative predictive ability of the autoregressive growth model with the model augmented with FCIs at one- and four-quarter horizons for the first quarter of 2009. In the case of the global financial crisis, examining the behavior of sampled countries' FCIs through 2008 is revealing. Close examination shows why the forecasting gain differs once the information set is augmented with FCIs at different time horizons. In the first quarter of 2009, GDP growth for most countries was among the worst in their recent economic history. The Lehman Brothers bankruptcy, at the beginning of the fourth quarter of 2008, was the bellwether for a swift and severe deterioration in financial conditions. Risk spreads and market volatility increased steeply, and asset values crashed. The information emanating from FCIs throughout the fourth quarter of 2008 clearly signaled potential negative fallout for economic activity. By contrast, economic indicators took additional time to catch up to the actual magnitude of the decline.

Figure 3.7. Probability Densities of GDP Growth for the Depths of the Global Financial Crisis
(Probability)

Accounting for financial conditions generates a more pessimistic outlook for risks to growth one quarter before 2009:Q1.



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The figure displays conditional probability distributions of one-quarter-ahead GDP growth based on a parametric, T-skew density, fitted over quantile regression estimates as described in Annex 3.3. In particular, it includes two conditional distributions of growth based on two forecasting models that use either growth or growth and financial conditions indices (FCIs) to predict future growth (in 2009:Q1). The figure also includes the realized values of GDP growth (black vertical line). Blue density = model with single regressor (one-quarter-lagged GDP growth); red density = model with two regressors (one-quarter-lagged GDP growth and one-quarter-lagged FCI).

and macroeconomic crises well. A good test of the predictive contribution of financial indicators *for such growth episodes* would be to examine how their addition to the conditioning information set would change the likelihood assigned to the realized (bad) growth outcome at various horizons.

[17]Results are presented for a selection of advanced and emerging market economies in Tables 3.1–3.3, even though similar results are obtained for other sampled countries that experienced a recession at the time of the global financial crisis. Results for countries that did not experience an economic contraction suggest that the model augmented with FCIs does not generate false alarms—that is, significantly lower conditional probability of a recession at one- and four-quarter forecast horizons.

Table 3.1. Forecast of GDP Growth Distribution for the Global Financial Crisis with and without Financial Conditions Indices

(Cumulative probability of actual 2009:Q1 growth outturn, percent)

Selected Advanced Economies				Selected Emerging Market Economies			
	Real-time FCI Augmented	FCI Augmented	Autoregressive		Real-time FCI Augmented	FCI Augmented	Autoregressive
Germany				**Brazil**			
One quarter ahead for 2009:Q1	5.4	2.4	0.0	One quarter ahead for 2009:Q1	35.5	39.6	7.5
Four quarters ahead for 2009:Q1	0.1	0.4	0.0	Four quarters ahead for 2009:Q1	4.2	5.0	5.5
Sweden				**Chile**			
One quarter ahead for 2009:Q1	6.5	5.9	4.8	One quarter ahead for 2009:Q1	6.4	8.0	2.6
Four quarters ahead for 2009:Q1	0.0	0.8	0.5	Four quarters ahead for 2009:Q1	4.0	1.7	2.0
United Kingdom				**South Africa**			
One quarter ahead for 2009:Q1	29.8	29.5	5.8	One quarter ahead for 2009:Q1	7.2	4.6	0.8
Four quarters ahead for 2009:Q1	0.8	2.8	1.5	Four quarters ahead for 2009:Q1	5.3	6.2	1.6
United States				**Turkey**			
One quarter ahead for 2009:Q1	46.7	30.3	8.5	One quarter ahead for 2009:Q1	31.5	27.1	5.3
Four quarters ahead for 2009:Q1	2.6	4.0	4.2	Four quarters ahead for 2009:Q1	3.5	2.3	2.8

Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.

Note: The table depicts the cumulative probabilities of a growth outcome in 2009:Q1 of less than or equal to the actual growth outturn (quarter over quarter, annualized) in that period drawn from conditional density forecasts of GDP growth made four quarters earlier (that is, in 2008:Q1). The left column depicts probabilities from the model with financial conditions indices (FCIs) estimated with information available in real time. The middle column depicts probabilities from the model with FCIs estimated with full in-sample information. The right column depicts probabilities from the autoregressive model of GDP growth. Autoregressive = quantile regression of one-year-ahead GDP growth on current quarter GDP growth; FCI augmented = quantile regression of one-year-ahead GDP growth on current quarter GDP growth and FCI.

Table 3.2. Market Consensus Forecasts for the Global Financial Crisis Were Considerably More Optimistic Than Forecasts Based on Financial Conditions

	Growth Forecasts Conditional on Lagged GDP and FCI		Consensus Growth Forecasts		Growth Outturn in 2009:Q1[1]
	2008:Q1	2008:Q4	2008:Q1	2008:Q4	
Brazil	3.1	–4.3	4.6	2.1	–6.9
Canada	1.7	–5.3	1.7	–0.1	–8.8
France	1.9	–1.2	1.6	–0.6	–6.4
Mexico	2.6	–3.6	2.8	–0.1	–14.7
South Africa	2.7	–2.0	4.7	2.7	–6.1
Switzerland	1.9	–2.0	2.8	–1.6	–5.5
Turkey	3.4	–7.4	4.8	0.8	–15.2
United States	1.9	–3.8	1.6	–1.3	–5.4

Sources: Bloomberg Finance L.P.; Consensus Economics; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.

Note: Columns 2 and 3 of the table denote, respectively, the conditional mean forecasts for (quarter over quarter, annualized) GDP growth in 2009:Q1 made one quarter and one year earlier based on an ordinary least squares regression of future GDP growth on current quarter FCI and GDP growth. Columns 4 and 5 denote market consensus forecasts for 2009:Q1 made one quarter and four quarters earlier, respectively. Column 6 depicts the actual growth outturn. FCI = financial conditions index.

[1]Based on data available as of August 3, 2017.

Table 3.3. Forecast of GDP Growth Distribution for the Global Financial Crisis: Comparing Partitioned and Univariate Financial Conditions Indices with Autoregressions
(Cumulative probability of actual 2009:Q1 growth outturn, percent)

Selected Advanced Economies					Selected Emerging Market Economies				
	Real-time Partitioned Financial Variables	Partitioned Financial Variables	FCI Augmented	Autoregressive		Real-time Partitioned Financial Variables	Partitioned Financial Variables	FCI Augmented	Autoregressive
Germany					**Brazil**				
Four quarters ahead for 2009:Q1	0.8	0.7	0.4	0.0	Four quarters ahead for 2009:Q1	14.0	6.7	5.0	5.5
Sweden					**Chile**				
Four quarters ahead for 2009:Q1	7.1	5.7	0.8	0.5	Four quarters ahead for 2009:Q1	12.7	10.4	1.7	2.0
United Kingdom					**South Africa**				
Four quarters ahead for 2009:Q1	6.4	5.0	2.8	1.5	Four quarters ahead for 2009:Q1	5.4	7.3	6.2	1.6
United States					**Turkey**				
Four quarters ahead for 2009:Q1	24.7	19.1	4.0	4.2	Four quarters ahead for 2009:Q1	7.4	4.4	2.3	2.8

Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: The table depicts the cumulative probabilities of a growth outcome in 2009:Q1 of less than or equal to the actual growth outturn (quarter over quarter, annualized) in that period drawn from conditional density forecasts of GDP growth made four quarters earlier (that is, in 2008:Q1) according to the four alternative methodologies. Autoregressive = quantile regression of one-year-ahead GDP growth on current quarter GDP growth; FCI = financial conditions index; FCI augmented = quantile regression of one-year-ahead GDP growth on current quarter GDP growth and FCI; partitioned financial variables = quantile regression of one-year-ahead GDP growth on current quarter GDP growth and subindices of financial indicators.

This explains why autoregressive-conditional quantile forecasts were behind the curve, even at the end of 2008. A few quarters earlier, in early 2008, FCIs had risen from their boom-time lows but were only at their historical averages (for emerging market economies) or at levels corresponding to recessions significantly milder than the outturn of the first quarter of 2009 (for advanced economies). Consequently, one year ahead, conditioning on FCIs does not result in significantly different predictions of growth during the global financial crisis relative to either consensus forecasts or autoregressive-conditional quantile forecasts.

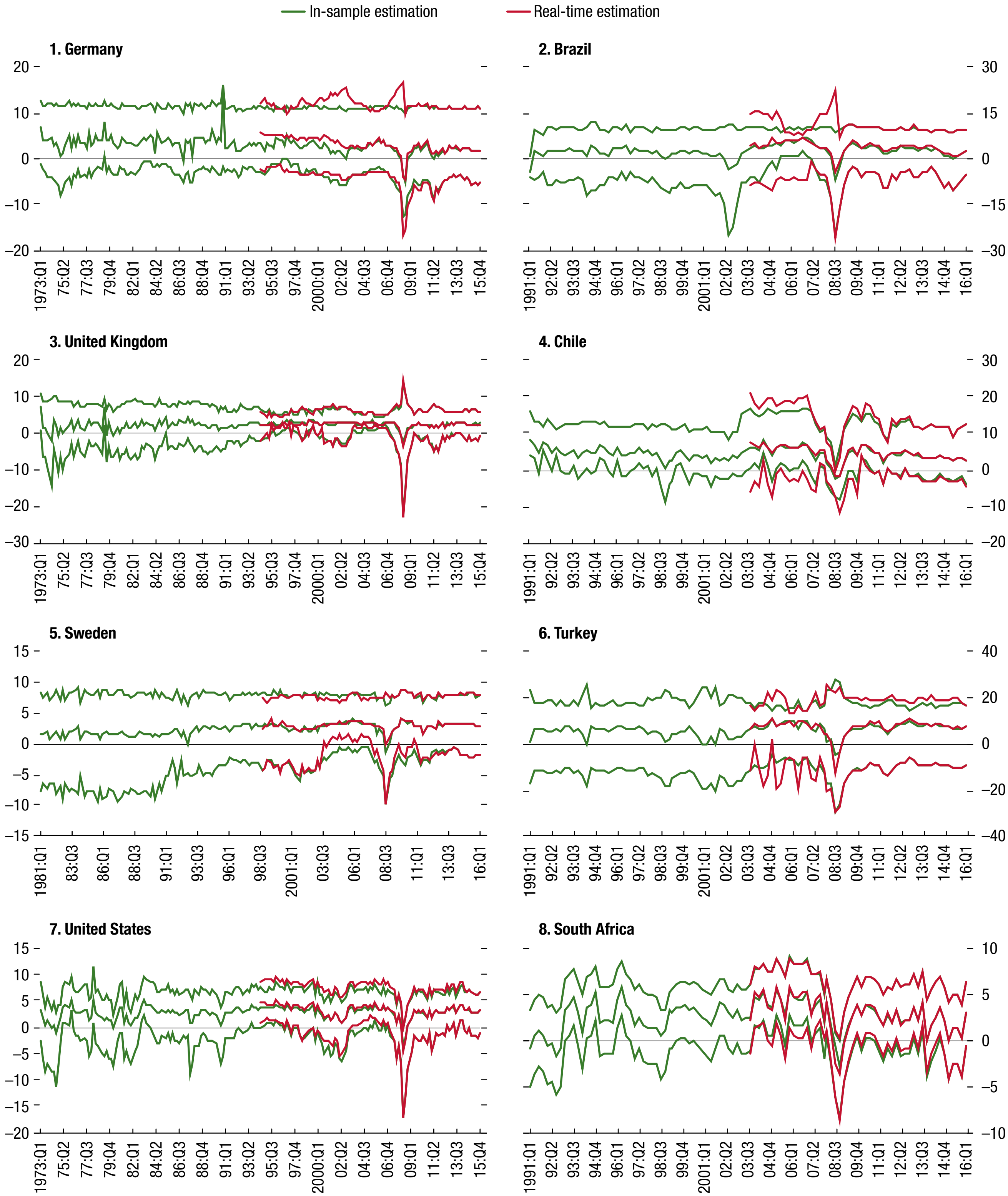
Partitioning the FCI constituents into subindices enables the forecasts conditioned on financial indicators to regain relative predictive gains over longer time horizons in several countries (Table 3.3).[18] One-year-ahead conditional forecasts for annual growth assign significantly higher likelihood to growth outcomes less than or equal to the outturn of the first quarter of 2009 when the forecasts are based on information in financial indicators than when based only on lagged GDP growth. This is the likely consequence of separating credit aggregates from asset prices, thereby allowing their information to gain greater weight at horizons beyond one quarter.

Real-time conditional density forecasts of economic growth are almost identical to those reported above for in-sample forecasts (Figures 3.8 and 3.9). Hence, using information in FCIs and in partitioned financial indicators available only up to one to four quarters earlier than the first quarter of 2009 would result in conditional likelihoods being assigned to the actual growth outcomes that are very similar to those obtained through in-sample forecasts using financial indicators (Tables 3.1 and 3.3).[19]

[18]The contribution of each financial indicator to its group subindex is determined according to a methodology designed to improve forecast performance as discussed in Annex 3.2.

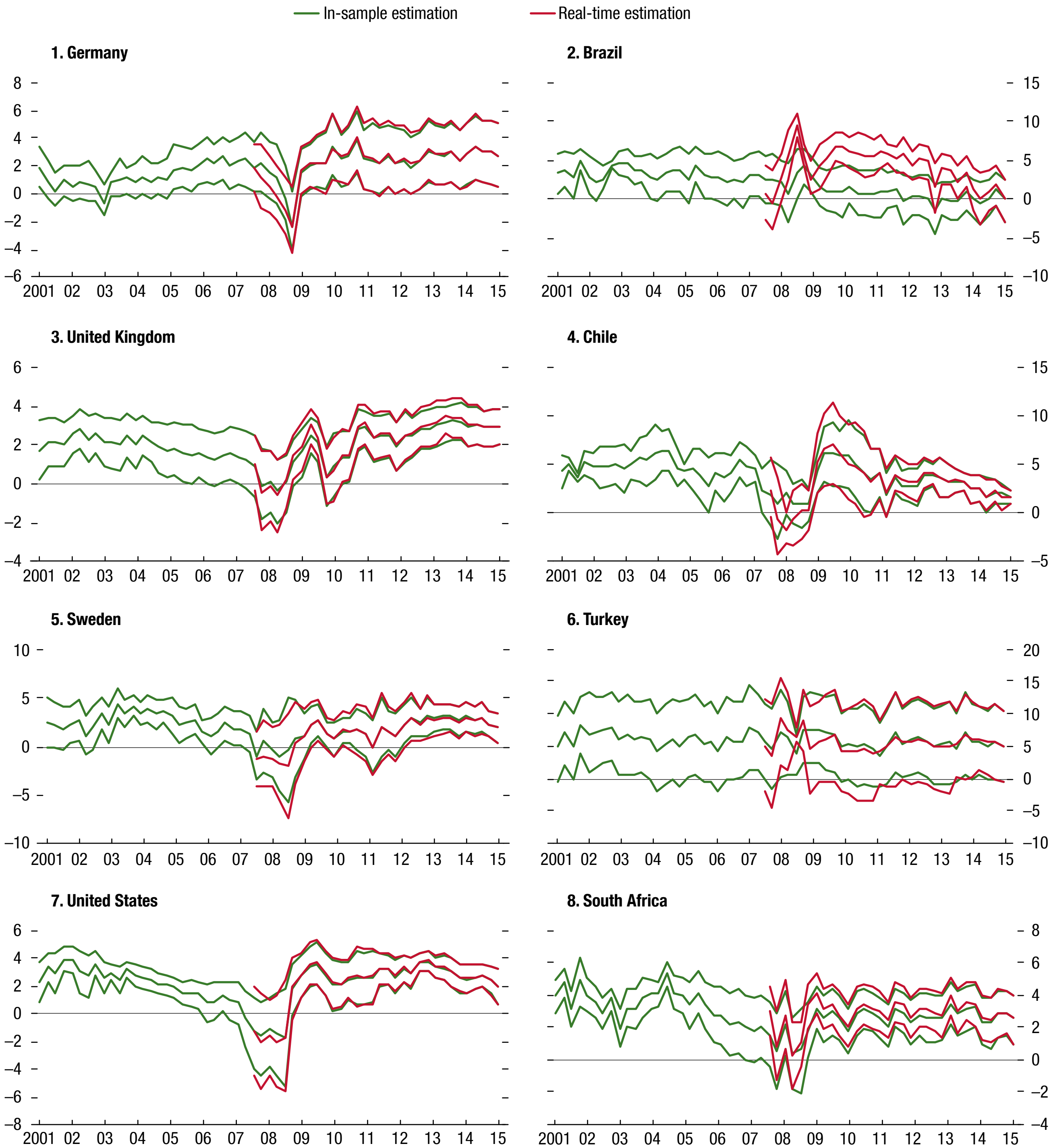
[19]This is implied by the fact that real-time forecasts of the quantiles of future GDP growth obtained through recursive estimation are almost identical to (or, below the median quantile, often lower than) those obtained through the in-sample forecasts. The fact that a majority of financial indicators are available only from the mid-1990s to the mid-2000s, especially for emerging market economies, prevents backtesting of the model's forecasting ability relative to earlier crisis-related recessions, for example, in Sweden (1990–92), Mexico (1994), east Asia (1997), and Turkey (2000–01), among others. More generally, low-frequency and limited time series data on real and financial variables preclude implementation with sufficient power of appropriate out-of-sample forecast evaluation tests described in Corradi and Swanson 2006 and Komunjer 2013.

Figure 3.8. In-Sample and Recursive Out-of-Sample Quantile Forecasts: One Quarter Ahead
(Percent)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: This figure shows the estimates of the 5th (bottom), 50th (middle), and 95th (top) quantiles of GDP growth based on the quantile regression model where one-quarter-ahead GDP growth is regressed on current date financial conditions index and GDP growth.

Figure 3.9. In-Sample and Recursive Out-of-Sample Quantile Forecasts: Four Quarters Ahead
(Percent)



Sources: Bloomberg Finance L.P.; Haver Analytics; IMF, Global Data Source and World Economic Outlook databases; Thomson Reuters Datastream; and IMF staff estimates.
Note: This figure shows the estimates of the 25th (bottom), 50th (middle), and 75th (top) quantiles of GDP growth based on the quantile regression model with partitioned financial indicators replacing the univariate financial conditions index.

This augurs well for the parameter stability of the chapter's forecast model, demonstrating that its forecasts and relative predictive ability are not an artifact of incorporating events such as the global financial crisis into estimates of its parameters.

Policy Implications

The chapter's findings underscore the importance of policymakers maintaining heightened vigilance regarding risks to growth during periods of benign financial conditions that may provide a fertile breeding ground for the accumulation of financial vulnerabilities. Changes in the domestic price of risk appear to be potent signals of imminent threats to growth and can be useful for swift deployment of monetary easing and crisis-management policy actions. Incorporating information in slower-moving indicators could help better calibrate countercyclical policies, even though doing so systematically would require combining the information derived from the models described in this chapter with appropriate structural models.

This chapter develops a new macroeconomic measure of financial stability by linking financial conditions to the probability distribution of future GDP growth. Since policymakers care about the whole distribution of future GDP growth, linking the state of the financial system to such a distribution would enhance macro-financial surveillance. Policymakers would be able to specify bad outcomes in terms of their risk preference or tolerance and undertake appropriate action based on the information provided by financial conditions. Thus, the new modeling approach can be a powerful tool for forecasting and policy development.

Financial conditions contain useful information with which to help forecast risks to economic growth at short- and medium-term horizons. Thus, the tools used and developed in this chapter can help policymakers assess the risks to the real economy associated with various states of the financial system. For example, at the current juncture, elevated leverage signals downside risks to growth in the medium term, although in the short term, this risk is mitigated by the low price of risk. However, a scenario of rapid decompression in spreads and an increase in financial market volatility would add to the risks arising from leverage, significantly worsening the growth outlook.

Policymakers could use the information provided by such a surveillance framework to identify imminent threats and take swift countervailing action over very short horizons. If a rapid increase in the price of risk at a time of elevated leverage or balance sheet mismatches indicates an imminent threat to the economy, policymakers can quickly ease monetary policy and deploy a wide range of crisis-management and -prevention measures to prevent tail events or reduce their magnitude. During the global financial crisis, bilateral and multilateral swap lines, general creditor guarantees, asset purchase programs, and emergency liquidity facilities, among others, were marshalled by a number of countries at relatively short notice.

The framework developed in this chapter could potentially help policymakers design policy actions to respond in a timely manner to threats to financial stability indicated by changes in financial conditions. It is natural to think of calibrating policy actions on the state of financial conditions—much as monetary policy action is calibrated to information on inflation and output under standard Taylor rules. For example, countercyclical macroprudential tools, such as bank capital buffers and limits on loan-to-value ratios, could be designed and calibrated to contain the growth of financial vulnerabilities in the presence of loose financial conditions. In this regard, the estimated forecast relationships from the GDP growth-at-risk model of this chapter can also be used to calibrate structural models that are amenable to counterfactual analysis and policy development.[20]

Practical implementation of forecasting of risks to growth based on financial conditions will require data gaps to be closed. This need strengthens the case for greater data-gathering efforts. It also points to a need for continuous calibration of these types of models as data gaps gradually close and for incorporation of country-level information that may substitute for the lack of standard financial indicators. In this way, policymakers and others could significantly improve on the forecasting power of the models presented here by incorporating rich country-level information to complement the models' broad financial indicators. As local financial markets undergo structural developments, and authorities consider certain financial indicators to

[20]One option could be to use the conditional density forecasts of GDP growth to calibrate the higher moments (for example, conditional volatility or skewness) of structural models that embed financial accelerator mechanisms such as the one described in Annex 3.1.

be increasingly relevant, these could also be gradually incorporated into the analysis.[21]

Annex 3.1. Financial Vulnerabilities and Growth Hysteresis in Structural Models[22]

An Illustrative Simulation

A simulation exercise of a structural model is conducted to illustrate the nonlinear response of output growth to shocks depending on the level of financial vulnerabilities. The exercise shows that embedding an occasionally binding funding constraint on borrowers in an otherwise standard New Keynesian (NK) open economy structural model is sufficient to generate two key stylized facts. These are, first, that the steady-state probability distribution of GDP growth is negatively skewed and, second, that asset prices and credit aggregates are leading indicators of risks to GDP growth.

In the presence of financial frictions, the response of output growth to shocks is highly nonlinear. Recent advances in macroeconomic theory have clarified the importance of financing constraints on borrowers and intermediaries in generating this response. In their seminal contributions, Bernanke and Gertler (1989); Kiyotaki and Moore (1997); and Bernanke, Gertler, and Gilchrist (1999) clarified the role of credit market frictions in determining fluctuations in real economic activity. Their linear real business cycle models embed a *financial accelerator* mechanism in which endogenous developments in credit markets propagate and amplify shocks to the real economy. Although these models explain how financial frictions increase the amplitude of real business cycles, they do not shed light on how and when they can increase the duration of those cycles or generate extreme, unlikely negative outcomes (asymmetry, or *tail risk*). The key insight of recent advances in business cycle theory is that this outcome depends on individual financial decisions of banks, firms, and households that fail to take into consideration dynamic credit supply externalities implied by their decisions. That is, individual borrowers fail to take into account the fact that once aggregate leverage is sufficiently high, shocks can activate *occasionally binding collateral constraints* (OBCCs). This, in turn, can generate a vicious cycle of deleveraging and negative asset price spirals that clog credit intermediation, consumption, investment, and growth.[23]

The simulation exercise embeds an OBCC into an NK open economy dynamic general equilibrium model. The OBCC is modeled as in Kiyotaki and Moore 1997. To tease out implications for optimal policy, nominal frictions based on an open economy NK model are incorporated in the spirit of Galí and Monacelli 2005. The main features of the model are as follows: Households are endowed with tradable goods as in Bianchi 2011, while they produce nontradables using capital and labor. Households maximize their lifetime utility by choosing an intertemporal portfolio of tradable and nontradable goods for consumption and supplying labor to the production process. Their borrowing must be lower than a fixed fraction of their capital value (that is, there is a collateral constraint). The nontradables sector is monopolistically competitive, and price setting is subject to nominal frictions. Asset prices are determined under a fixed supply of capital. Nominal interest rates are set under a standard Taylor rule responding to inflation and output. The exchange rate is pinned down by the uncovered interest parity condition. The parameters are calibrated based on standard values in the literature of an OBCC model and an open economy NK model, including Bianchi 2011 and Galí and Monacelli 2005.

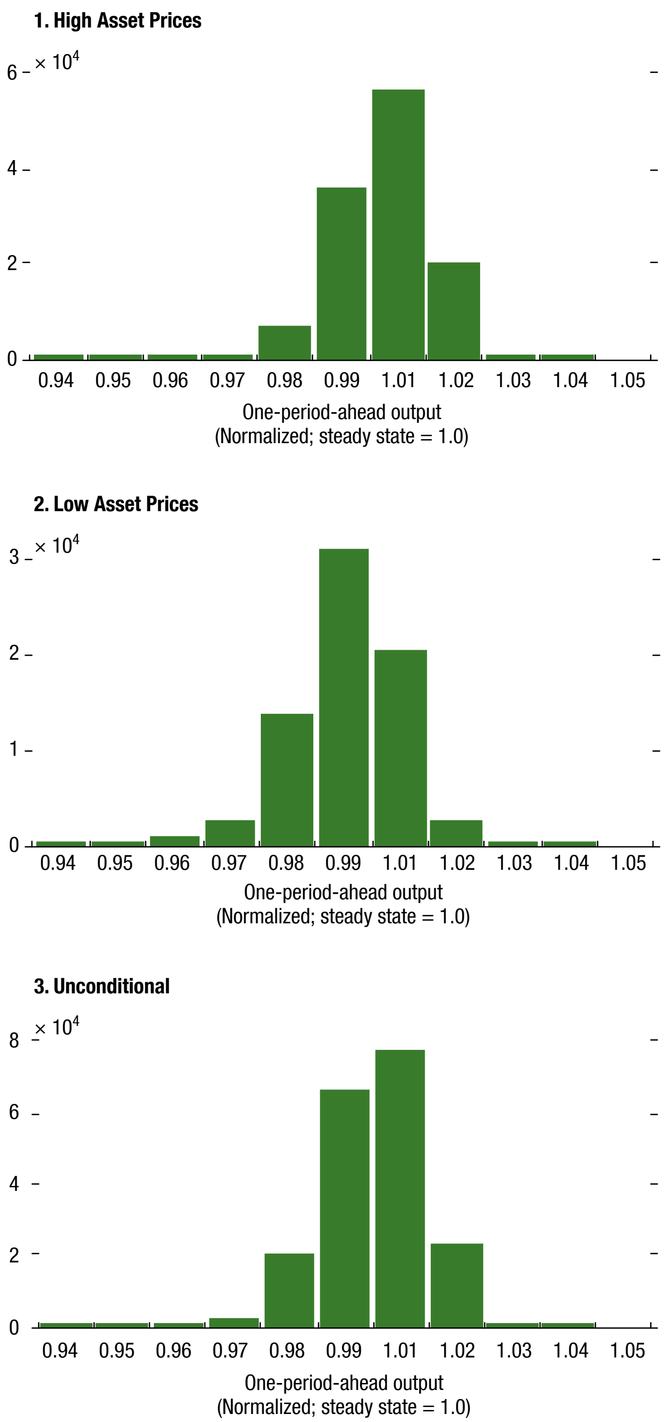
The simulated density of future output is shown to be negatively skewed; that is, it has a fat left tail, indicating a greater risk of severe recession. The unconditional distribution of future output (Annex Figure 3.1.1, panel 3) is negatively skewed—the skewness measure, at –1.51, is statistically significant. In the simulation, as in reality, the collateral constraint does not typically bind. Thus, the evolution of all economic variables, including output, is standard for the most part. However, when the OBCC binds (a rare event), output and asset prices decline significantly because

[21]The methodology developed in this chapter is used to model the impact of financial vulnerabilities on GDP growth. It is flexible in the inputs it can receive. In countries where risks to the real economy posed by amplifiers, whether real or fiscal, are not traded in deep financial markets, corresponding nonfinancial indicators could also be used as inputs.

[22]Prepared by Mitsuru Katagiri. (This annex is a summary of Katagiri, forthcoming.)

[23]For models embedding OBCCs on end-borrowers, see Bianchi 2011; Korinek and Simsek 2016; and Bianchi and Mendoza, forthcoming. For OBCCs or value-at-risk constraints on intermediaries, see He and Krishnamurthy 2013 and Brunnermeier and Sannikov 2014.

Annex Figure 3.1.1. Conditional Densities of Growth with High and Low Asset Prices—One-Period-Ahead Forecasts
(Frequency)



Source: IMF staff estimates.

of the vicious cycle of asset fire sales and tighter credit conditions, and output suffers.

The simulation exercise clearly indicates the utility of conditioning the growth outlook on asset prices. Risk premiums in the simulation exercise are defined as the return on capital minus the inverse of the stochastic discount factor, as is standard.[24] Annex Figure 3.1.1 shows the conditional density of output in period t, given that the risk premium in period $t - 1$ is less than 30 basis points (the case of high asset prices depicted in panel 1) and more than 30 basis points (the case of low asset prices depicted in panel 2). Those two panels indicate that when risk premiums rise (equivalently, when asset prices fall), the conditional density of one-period-ahead output shifts to the left and becomes negatively skewed. Higher risk premiums predict a lower average value of one-period-ahead output and a more pessimistic risk outlook (fatter left tail).

Asset prices and credit aggregates can also be useful leading indicators of recessions or financial crises. The relationship between one-period-ahead output and risk premiums (Annex Figure 3.1.2, panel 1) indicates that the lower quantile of output declines significantly with rising risk premiums, whereas its upper quantile is significantly less sensitive. The relationship between one-period-ahead output and the credit-to-GDP ratio shows that a financial crisis occurs only when the ratio is at a historically high level (Annex Figure 3.1.2, panel 2). Finally, risk premiums and credit-to-output ratios are significantly higher than their steady-state values for several periods before a crisis (Annex Figure 3.1.3).

Calibrating Policy Rules to Attenuate Risks to Growth from Financial Vulnerability

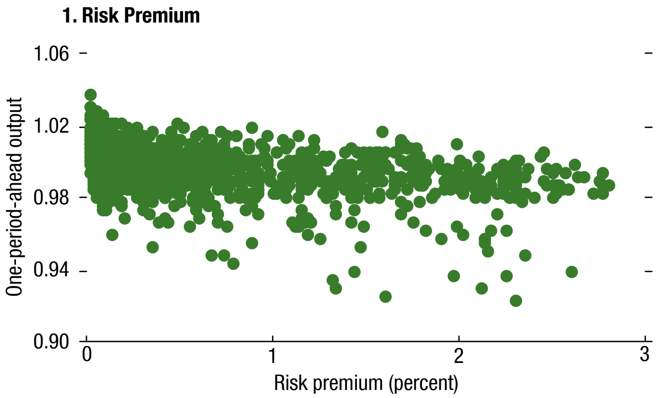
Macroprudential policy contingent on the state of financial conditions can mitigate the adverse real effects of financial crises. The decentralized equilibrium described in the previous section of this annex is *not* socially optimal because agents fail to take into consideration the negative systemic externalities of their leverage choices on asset prices. Borrowers' resulting excess leverage increases the frequency of financial crises.

[24]Note that risk premiums based on this definition are not directly observable in the data, but are conceptually close to the excess return of risk assets as defined in Gilchrist and Zakrajšek 2012 and hence can be calculated from financial market data.

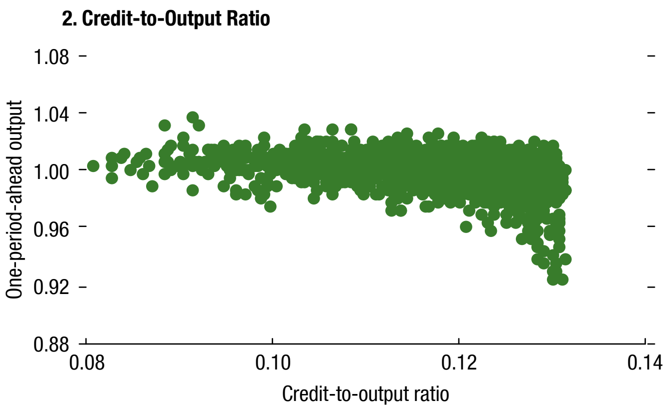
Annex Figure 3.1.2. One-Period-Ahead GDP and Financial Conditions

(Normalized; steady state = 1.0)

Increasing risk premiums signal a more pessimistic growth outlook ...



... as does elevated leverage.



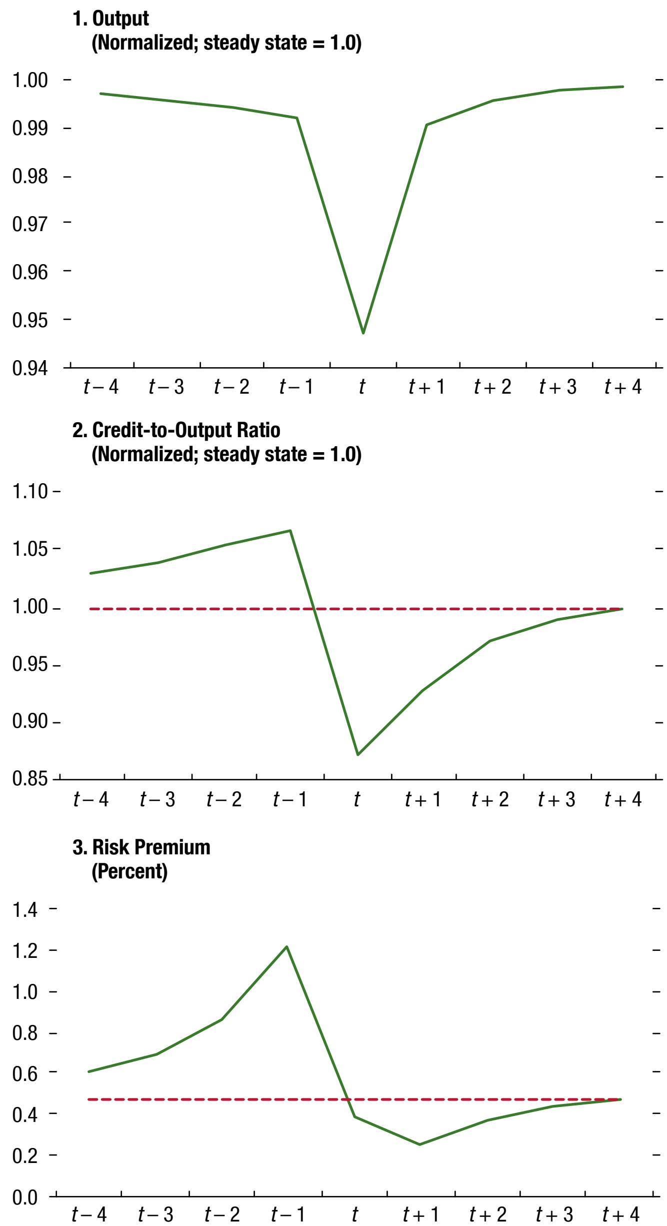
Source: IMF staff estimates.

Bianchi (2011) and Bianchi and Mendoza (forthcoming) show that a macroprudential tax (that is, a tax on debt before the crisis) that is contingent on the state of financial conditions can prevent excess leverage and implement the socially optimal outcome as a decentralized equilibrium. This socially optimal outcome can also be implemented by a regulation on loan-to-value (LTV) ratios.

Once the optimal state-contingent macroprudential policy (taxes on debt or LTV regulation) is introduced, vulnerability to a recession (as measured by the negative skewness of the output distribution) is significantly mitigated. In the *baseline simulation* of the equilibrium without optimal macroprudential policy,

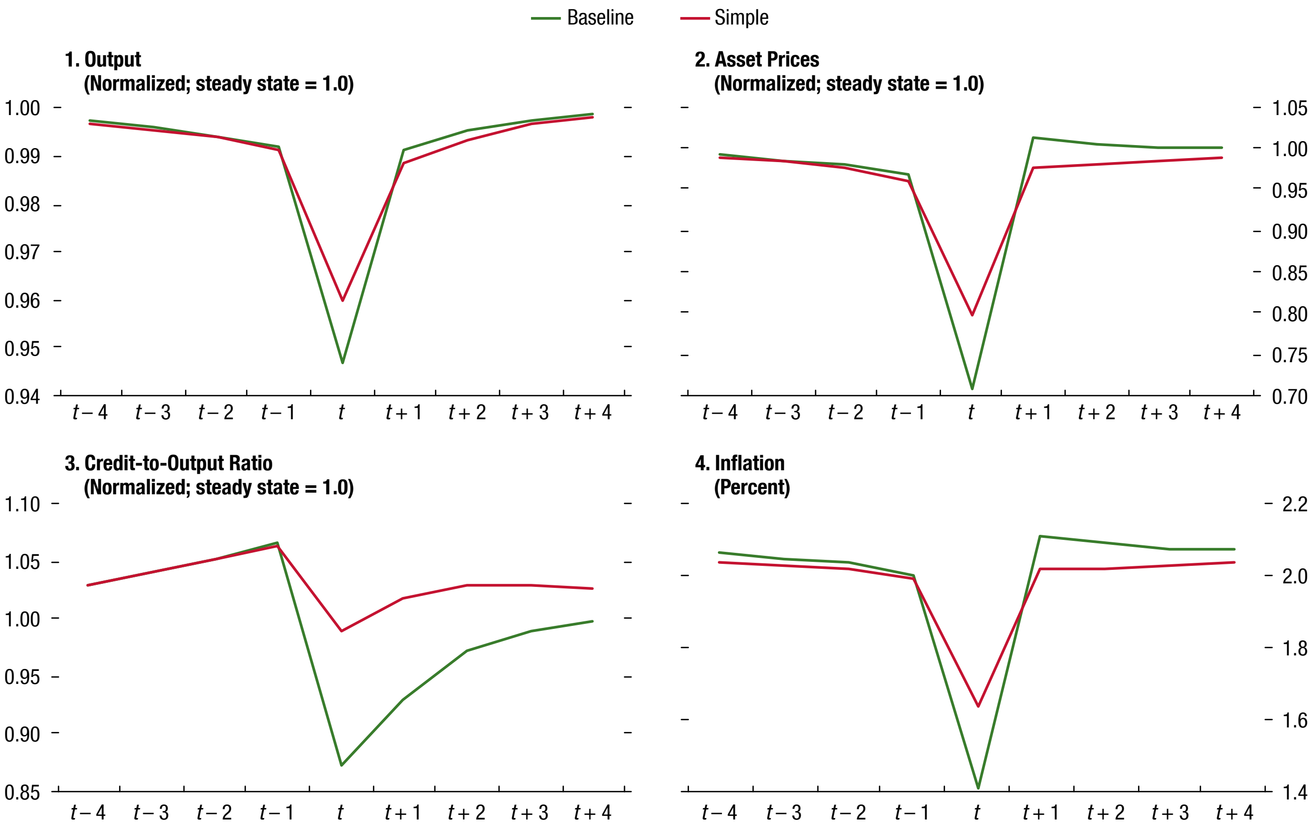
Annex Figure 3.1.3. Asset Prices and Credit Aggregates before and after a Financial Crisis

Severe economic contractions are preceded by several periods of excessive leverage and, shortly before the crisis, by sharply rising risk premiums.



Source: IMF staff estimates.
Note: The crisis happens in period 5 (t) in the figures. The crisis is defined as a period in which output declines by more than 3 percent. The red dashed lines denote steady-state values.

Annex Figure 3.1.4. Simple Debt Tax Ameliorates Risk of Leverage-Induced Recessions



Source: IMF staff estimates.

the probability of a recession driven by a financial crisis is 1.3 percent, and the skewness of the density of future GDP growth at –1.51 is statistically significant. Implementation of the state-contingent debt tax or state-contingent LTV regulation reduces these values to, respectively, 0.5 percent and –0.66.

A simple policy rule conditioned on financial indicators comes close to implementing the optimal macroprudential policy. The optimal policy itself is a complex nonlinear function of state variables and is probably too complicated to implement in practice.[25] Fortuitously, a simple rules-based macroprudential policy responding to vulnerability measures does a good job of mitigating the harmful effects of financial crises. Risk premiums are used to improve the performance of a simple rules-based macroprudential policy because they have predictive power for the crisis. Annex Figure 3.1.4 compares the evolution of real and financial indicators under a simple policy rule whereby debt taxes are a linear function of risk premiums to the baseline equilibrium. Policy based on a simple linear rule delivers almost the same performance as the optimal policy, implying that financial conditions such as risk premiums are useful for conducting macroprudential policies in practice.[26]

[25]The nonlinearity stems from the fact that policymakers should raise borrowing costs through taxes or LTV regulations *only* when a crisis is predicted.

[26]There are two caveats. First, all crises in the OBCC model are caused by a simple collateral constraint, whereas many other factors can contribute to financial crises. Second, the model assumes that policymakers can immediately respond to vulnerabilities. If there is a delay in policy reactions or their transmission to the real economy, the policy implications may be different.

Annex Table 3.2.1. Country Coverage

Australia	Germany	Mexico	Turkey
Brazil	India	Russia	United Kingdom
Canada	Indonesia	South Africa	United States
Chile	Italy	Spain	
China	Japan	Sweden	
France	Korea	Switzerland	

Source: IMF staff.

Annex 3.2. Estimating Financial Conditions Indices[27]

Univariate Financial Conditions Indices

A simple way to build a summary measure of financial conditions is to construct univariate financial conditions indices (FCIs) following the approach in the April 2017 GFSR, although with some important modifications. The main change is that the coverage of financial indicators is expanded to include additional information relevant to assessing domestic financial vulnerabilities. FCIs will therefore also include variables that summarize global risk sentiment (Chicago Board Options Exchange Volatility Index [VIX], Merrill Lynch Option Volatility Estimate [MOVE] Index), credit aggregates that directly indicate the level of financial vulnerability in the economy, and commodity prices and exchange rates that may influence and reflect the ease of funding and financial constraints—for example, by altering borrowers' net worth.[28]

Following the methodology presented in Annex 3.1 of the April 2017 GFSR, FCIs are reestimated for 11 advanced economies starting in 1973 and for 10 emerging market economies starting in 1991. A set of 19 financial indicators is used to capture both domestic and global developments influencing a country's financial conditions (see Annex Table 3.2.1 for country coverage and Annex Table 3.2.2 for variables included and data sources). The FCIs are estimated based on Koop and Korobilis 2014 and build on the estimation of the time-varying parameter vector autoregression model of Primiceri (2005) and dynamic factor models of Doz, Giannone, and Reichlin (2011).[29] This approach has two advantages. First, it can control for current macroeconomic conditions. Second, it allows for dynamic interaction between the FCIs and macroeconomic conditions, which can also evolve over time. The model takes the following form:

$$x_t = \lambda_t^y Y_t + \lambda_t^f f_t + u_t,$$
$$\begin{bmatrix} Y_t \\ f_t \end{bmatrix} = B_{1,t}\begin{bmatrix} Y_{t-1} \\ f_{t-1} \end{bmatrix} + B_{2,t}\begin{bmatrix} Y_{t-2} \\ f_{t-2} \end{bmatrix} + \ldots + \varepsilon_t, \qquad \text{(A3.2.1)}$$

in which x is a vector of financial indicators, Y is a vector of macroeconomic variables of interest (including real GDP growth and inflation), λ_t^y are regression coefficients, λ_t^f are the factor loadings, and f_t is the latent factor, interpreted as the FCI.

Univariate FCIs offer a parsimonious way of summarizing the information in several financial indicators, which could be advantageous from a forecasting perspective because it can help reduce parameter uncertainty. However, the weight of each variable is not necessarily driven by economic considerations of relative importance as suggested either by theory or by country-specific characteristics. For example, movements in asset prices may be effective in pinpointing risks at short horizons, but slower-moving credit aggregates are likelier to yield more information at longer time horizons. Moreover, while asset prices are likely to be an adequate summary of financial vulnerabilities in some advanced economies, credit aggregates may possess significantly greater information content in emerging market economies. Consequently, financial indicators need not receive the same weight across different time horizons and countries; therefore, as described in the second section of this annex, the chapter also uses an approach that seeks to exploit the information content of

[27]Prepared by Romain Lafarguette and Dulani Seneviratne.

[28]An important reason to expand coverage to aggregates is that beyond a few advanced economies, it is unlikely that developments in asset prices provide an adequately encompassing and timely summary of the information regarding vulnerabilities that is contained in these financial aggregates. Thus, conditioning directly on the information content of the aggregates may improve the accuracy of forecasts of the risk outlook for growth.

[29]The FCIs are estimated using Koop and Korobilis' (2014) code (https://sites.google.com/site/dimitriskorobilis/matlab).

Annex Table 3.2.2. Data Sources

Variables	Description	Source
Domestic-Level Variables		
Term Spreads	Yield on 10-year government bonds minus yield on three-month Treasury bills	Bloomberg Finance L.P.; IMF staff
Interbank Spreads	Interbank interest rate minus yield on three-month Treasury bills	Bloomberg Finance L.P.; IMF staff
Change in Long-Term Real Interest Rate	Percentage point change in the 10-year government bond yield, adjusted for inflation	Bloomberg Finance L.P.; IMF staff
Corporate Spreads	Corporate yield of the country minus yield of the benchmark country; JPMorgan CEMBI Broad is used for emerging market economies where available	Bloomberg Finance L.P.; Thomson Reuters Datastream
Equity Returns (local currency)	Log difference of the equity indices	Bloomberg Finance L.P.
House Price Returns	Log difference of the house price index	Bank for International Settlements; Haver Analytics; IMF staff
Equity Return Volatility	Exponential weighted moving average of equity price returns	Bloomberg Finance L.P.; IMF staff
Change in Financial Sector Share	Log difference of the market capitalization of the financial sector to total market capitalization	Bloomberg Finance L.P.
Credit Growth	Percent change in the depository corporations' claims on private sector	Bank for International Settlements; Haver Analytics; IMF, International Financial Statistics database
Sovereign Spreads	Yield on 10-year government bonds minus the benchmark country's yield on 10-year government bonds	Bloomberg Finance L.P.; IMF staff
Banking Sector Vulnerability	Expected default frequency of the banking sector	Moody's Analytics, CreditEdge; IMF staff
Exchange Rate Movements	Change in US dollar per national currency exchange rate; for the United States, Bloomberg Finance L.P.'s DXY index is used	Bloomberg Finance L.P.; IMF, Global Data Sources and International Financial Statistics databases
Domestic Commodity Price Inflation	A country-specific commodity export price index constructed following Gruss 2014, which combines international commodity prices and country-level data on exports and imports for individual commodities; change in the estimated country-specific commodity export price index is used	Bloomberg Finance L.P.; IMF, Global Data Sources database; United Nations, COMTRADE database; IMF staff
Trading Volume (equities)	Equity markets' trading volume, calculated as level to 12-month moving average	Bloomberg Finance L.P.
Market Capitalization (equities)	Market capitalization of the equity markets, calculated as level to 12-month moving average	Bloomberg Finance L.P.; Thomson Reuters Datastream
Market Capitalization (bonds)	Bonds outstanding, calculated as level to 12-month moving average	Dealogic; IMF staff
Change in Credit to GDP	Change in credit provided by domestic banks, all other sectors of the economy, and nonresidents (in percent of GDP)	Bank for International Settlements; Haver Analytics; IMF staff
Real GDP Growth	Percent change in GDP at constant prices	IMF, World Economic Outlook database
Inflation	Percent change in the consumer price index	Haver Analytics; IMF, International Financial Statistics database
Global-Level Variables		
VIX	Chicago Board Options Exchange Market Volatility Index	Bloomberg Finance L.P.; Haver Analytics
MOVE	Merrill Lynch Option Volatility Estimate Index	Bloomberg Finance L.P.

Source: IMF staff.
Note: CEMBI = Corporate Emerging Markets Bond Index; DXY = Dollar Index Spot; MOVE = Merrill Lynch Option Volatility Estimate Index; VIX = Chicago Board Options Exchange Volatility Index.

Annex Table 3.2.3. Partitioning of Financial Indicators into Groups

	Price of Risk	Leverage	Foreign Shocks	Persistence
Financial and Real Indicators (when available)	Term spread Corporate spread Short-term rate Real long-term rate Sovereign spread Interbank spread Equity returns Equity historical volatility House price returns	Credit to GDP Credit growth (quarterly)	Bilateral exchange rate (US dollar to local currency) Commodity prices VIX[1]	GDP growth

Source: IMF staff.
[1] Except for the United States, for which VIX enters as a price-of-risk variable. VIX = Chicago Board Options Exchange Volatility Index.

financial indicators in a manner that is more sensitive to countries and time horizons.

Data Partitioning Based on Linear Discriminant Analysis

The individual financial indicators are aggregated into groups using linear discriminant analysis (LDA), a data-reduction technique (Annex Table 3.2.3). LDA aims to project a data set onto a lower-dimensional space while ensuring adequate separation of data into categories. LDA is similar to principal components analysis (PCA) in the sense that it maximizes the common variance among a set of variables, but it diverges from PCA by also ensuring that the linear combination of the variables discriminates across the classes of another categorical variable of interest. In the framework of the chapter, this categorical variable is a dummy variable, defined at the country level, equal to one when future GDP growth at a one-year horizon is below the 20th percentile of historical outcomes and equal to zero otherwise. Consequently, the loading on each individual financial indicator in the LDA is determined in a way that maximizes its contribution to discriminating between periods of low GDP growth and periods of normal GDP growth. This is convenient from the chapter's perspective because it allows for a link between financial indicators and GDP growth in the data-reduction process. By contrast, the PCA approach aggregates only information about the common trend among financial indicators.[30]

[30]LDA assumes independence of normally distributed data and homoscedastic variance among each class, although LDA is considered robust when these assumptions are violated. See Duda, Hart, and Stork 2001. See Izenman 2013 for a thorough exposition of the LDA technique.

Annex 3.3. The Conditional Density of Future GDP Growth[31]

Quantile Regressions

The estimation of the conditional density forecast is conducted through quantile projections.[32] This approach starts by using quantile regressions to directly estimate the conditional quantiles (q) of the forecast distribution of GDP growth (y) h quarters ahead, as a function of both its current level and current financial conditions (FC):

$$y_{t+h,q} = \beta^h_{f,q} FC_t + \beta^h_{y,q} y_t + \epsilon^h_{t,q}. \tag{A3.3.1}$$

In the baseline approach, FC corresponds to a predetermined univariate financial conditions index (FCI) constructed in the manner described in Annex 3.2.

The empirical model is subsequently modified to investigate the relative significance of asset prices, credit aggregates, and global or foreign factors in signaling risks to GDP growth in the near to medium term:

$$y_{t+h,q} = \alpha^h_{p,q} p_t + \beta^h_{a,q} Agg_t + \gamma^h_{y,q} y_t + \phi^h_{f,q} f_t + \epsilon^h_{t,q}, \tag{A3.3.2}$$

in which p, Agg, and f correspond to the principal components of the price of risk (asset prices and risk spreads),

[31]Prepared by Sheheryar Malik and Romain Lafarguette.

[32]For an introduction to quantile regression, see Koenker 2005. As highlighted by Komunjer (2013), quantile regressions rely on specific functional form assumptions and have some important advantages in forecasting the conditional distribution of the variable of interest. These include the desirability of the conditional quantile estimator as a predictor of the true future quantile; robustness of the estimation to extreme outliers and violations of normality and homoscedasticity of the errors; flexibility, allowing for time-varying structural parameters and the optimal weighting of predictors depending on country, horizon, and the relevant portion of the distribution; and the ability to avoid overfitting (compared with more complex models such as copulas and extreme value theory).

credit aggregates, and global or foreign variables (commodity prices, exchange rates, and global risk sentiment). This approach disentangles the contribution of changes in the price of risk from evolving credit aggregates and shocks to the external environment when it comes to forecasting risks to GDP growth. It thereby provides insight into which variables signal growth tail risks over various time horizons. This can help policymakers and others design a surveillance framework that seeks to embed information flowing in at different frequencies.

Deriving the Density Forecast

The quantile regression in equation (A3.3.1) delivers an estimate for the conditional quantile function (or inverse cumulative distribution function) h quarters ahead—that is, $\hat{y}_{t+h,q}\left(=\hat{\beta}^{h}_{f,q}FC_t+\hat{\beta}^{h}_{y,q}y_t\right)$. Given the noisiness of such estimates in practice, recovering the corresponding predictive probability density function will inevitably require smoothing of the quantile function. In this chapter, this is accomplished via fitting a parametric form skewed t distribution.[33]

For each quarter, the analysis attempts to pin down four parameters of the predictive density $\{\mu_{t+h}, s_{t+h}, v_{t+h}, \xi_{t+h}\}$ by minimizing the squared distance between the estimated quantile function, $\hat{y}_{t+h,q}$, and (theoretical) quantile function $y^{f}_{q}\left(\mu_{t+h}, s_{t+h}, v_{t+h}, \xi_{t+h}\right)$ corresponding to the above skewed t distribution (see Giot and Laurent 2003). The four parameters (μ, s, v, ξ) are, respectively, the location, scale, degrees of freedom, and the shape of skewed t distribution. Specifically, the 5th, 25th, 50th, 75th, and 95th percentiles are matched via

$$\{\mu_{t+h}, s_{t+h}, v_{t+h}, \xi_{t+h}\} = \underset{\mu_{t+h}, s_{t+h}, v_{t+h}, \xi_{t+h}}{\text{argmin}} \sum_q \left\{\hat{y}_{t+h,q} - y^{f}_{q}\left(\mu_{t+h}, s_{t+h}, v_{t+h}, \xi_{t+h}\right)\right\}^2,$$

in which $\mu_{t+h} \in \mathbb{R}$, $s_{t+h} > 0$, $v_{t+h} \geq 2$, and $\xi_{t+h} > 0$. Notwithstanding the skewness property, choice of a skewed t functional form is advantageous from the perspective of flexibility. For example, $v \rightarrow \infty$, $f(y; \mu, s, v, \xi)$ is characterized by tail properties resembling a Gaussian distribution. Moreover, the density is symmetric for $\xi = 1$.

[33]There are many choices for fitting a conditional density on the set of conditional quantiles. Adrian, Boyarchenko, and Giannone (2016) adopt a parametric approach focusing on a distribution family chosen a priori (t skewed), whereas De Nicolò and Lucchetta (2017) use a nonparametric approach. The functional form for the skewed t distribution is motivated by Fernandez and Steel (1998) and further explored and refined in Giot and Laurent 2003 and Lambert and Laurent 2002; see also Boudt, Peterson, and Croux 2008. Alternative specifications for the skewed t distribution are present in literature—for example, as put forth by Hansen (1994) and Azzalini and Capitanio (2003). These are essentially equivalent given a nonlinear transformation of the skewness parameter.

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