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The Term Structure of Growth-at-Risk

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Abstract

Using panel quantile regressions for 11 advanced and 10 emerging market economies, we show that the conditional distribution of GDP growth depends on financial conditions, with growth-at-risk (GaR)—defined as growth at the lower 5th percentile—more responsive than the median or upper percentiles. In addition, the term structure of GaR features an intertemporal tradeoff: GaR is higher in the short run; but lower in the medium run when initial financial conditions are loose relative to typical levels, and the tradeoff is amplified by a credit boom. This shift in the growth distribution generally is not incorporated when solving dynamic stochastic general equilibrium models with macrofinancial linkages, which suggests downside risks to GDP growth are systematically underestimated.

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I. INTRODUCTION

Financial conditions affect the expected growth distribution; but macroeconomic models and forecasting practices predominantly focus on expected mean growth, and usually do not model volatility or other higher moments of the distribution. This focus on conditional growth for estimations can be too narrow when volatility and skewness increase as growth weakens, and may lead to systematic underestimation of downside tail risks.

In this paper, we estimate the distribution of expected GDP growth for 21 countries using panel quantile regression methods. Our objectives are to measure the median and the lower 5th percentile of the distribution of expected real GDP growth—which we call growth-at risk (GaR)—and then how they change over the projection horizon as a function of financial conditions. Concretely, GaR is the conditional growth at the (lower) 5th percentile of the GDP growth distribution, and thus captures expected growth at a low realization of the GDP growth distribution. For example, higher growth and lower volatility would lead to a higher GaR, and lower growth and higher volatility would lead to a lower GaR. By also estimating the term structure, we can evaluate whether higher GaR achieved in the near term with loose financial conditions is long-lasting and sustainable.

We model empirically the distribution of future real GDP growth as a function of financial conditions, economic conditions, inflation, and credit growth for a panel of 11 advanced economies (AEs) and of 10 emerging market economies (EMEs).[2] This model builds on estimations for the United States in Adrian, Boyarchenko, and Giannone (2018). We also use local projections to estimate the dynamic response of GDP growth moments from 1 to 12 quarters, which allows us to explore the evolution of risk over the forecast horizon.

Figure 1 provides an illustration of the important role of financial conditions for the modeling of the distribution of growth and the implied intertemporal risk-return tradeoff. In particular, coefficient estimates on the financial conditions index (FCI) from panel quantile regressions for the lower 5th percentile and the median of the distribution of GDP growth (average quarterly growth for the cumulative period ending in quarters 1 through 12, at an annual rate) for AEs and EMEs, respectively, are shown. A higher FCI represents looser financial conditions. The positive coefficients in near-term quarters for both the 5th percentile and median indicate that the marginal effects of looser financial conditions are to significantly boost expected growth and reduce downside risk. But the decline in coefficients over the projection horizon suggests the impetus from initial looser financial conditions will decline or subtract from average expected cumulative growth in quarters further out, at about nine quarters and more. The decline is more pronounced for the 5th percentile than the median and

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[2] The 11 AEs include Australia, Canada, France, Germany, Great Britain, Italy, Japan, Spain, Sweden, Switzerland and the United States. The 10 EMEs include Brazil, Chile, China, India, Indonesia, Mexico, Russia, Turkey, South Africa, and South Korea. These countries are the complete set covered in Chapter 3 of the October 2017 IMF Global Financial Stability Report (GFSR).

illustrates the shifting expected growth distribution over the projection horizon. The significant reversal in the signs of the estimated coefficients on FCI for growth at the 5th percentile suggests there is an important intertemporal tradeoff associated with financial conditions.

Figure 1. Estimated Coefficients on FCI for GaR and Median Growth—AEs and EMEs
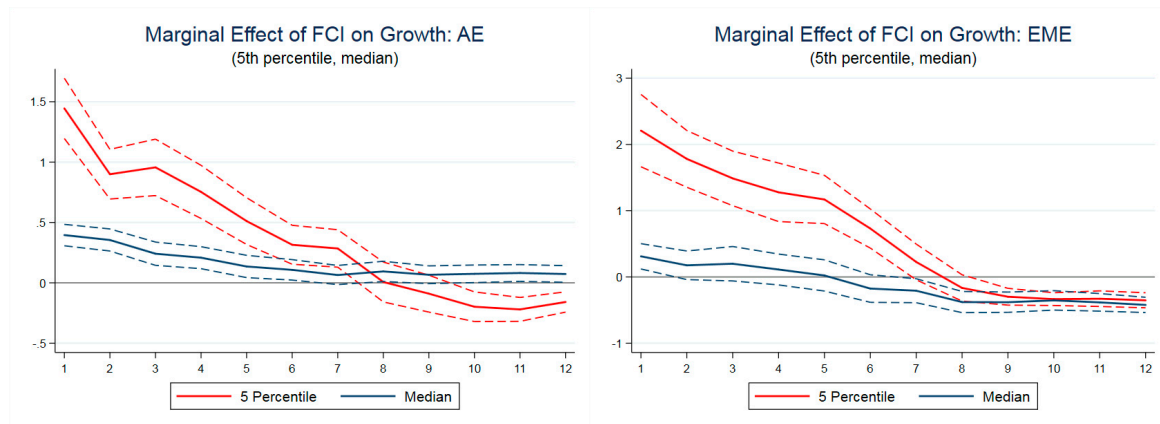
Source: IMF staff estimates.

Note: The figures plot the estimated coefficients on the financial conditions index (FCI) from panel quantile regressions for the median and the 5th percentile (GaR) for 1 to 12 quarters into the future. Higher FCI represents looser financial conditions. Estimates are based on local projection estimation methods, and standard errors are from bootstrapping techniques; bands represent plus and minus one standard deviation. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2017.

Our interpretation of these coefficients is that changes in the distribution of GDP growth reflect changes in the price of risk as measured by financial conditions. Changes in the price of risk can arise from financial frictions, such as regulatory capital constraints or value at risk (VaR) models, which tie together the price of risk and volatility via financial intermediaries (Adrian and Shin, 2014; He and Krishnamurthy, 2012, 2013). When financial conditions loosen and asset prices rise, constraints become less binding; GDP growth also increases and its distribution tightens. However, the lower price of risk and lower volatility can contribute to an increase in vulnerabilities, such as credit, which would amplify an adverse shock and lead to a sharper rise in volatility, referred to as the volatility paradox (Brunnermeier and Sannikov, 2014).

We allow for nonlinear effects of FCIs on the growth distribution through financial vulnerabilities that could amplify a negative shock. In particular, we evaluate whether the effect of loose financial conditions would be amplified by rapid credit growth. High credit growth has been shown to help predict the duration and severity of a recession (Jorda, Schularick, and Taylor, 2013), and the credit-to-GDP gap a predictor of recessions (Borio

and Lowe, 2002). We define a credit boom build-up by a dummy variable when both FCI and credit growth are in the top 30 percent of their respective distributions. The estimated coefficients on the dummy suggest that a credit boom in AEs forecasts significantly lower GaR in the medium term than when just financial conditions are loose; effects for EMEs are similar, but more modest in magnitude.

The addition of credit growth also helps to address a possible caveat of this framework, which is that the estimated effects of FCI on the conditional distribution of GDP growth may simply reflect the different speeds at which financial conditions and GDP growth respond to common negative shocks, where FCIs might incorporate news more quickly than the real economy. According to this argument, FCIs do not predict GDP growth, but FCI and GDP growth are correlated because of a common shock. However, if the effects of loose FCIs on growth also depend on high credit growth, the nonlinear results would be more consistent with models of endogenous risk-taking and amplification of shocks, rather than just different adjustment periods to a common shock. For a common shock, we would not expect that the predictive power of a low price of risk should be stronger with the presence of higher credit or credit growth.

The estimations indicate meaningful differences in the GaR term structure depending on the initial level of financial conditions. A key result is that GaR conditional on high FCI, and a credit boom is higher in the near term but lower in the medium term relative to GaR conditional on average FCI. For AEs, this difference is substantial. When FCIs are in the top 10 percent, GaR falls substantially, from about 0.5 percent to -2.5 percent between the short- and medium-term horizons, while the GaR for initial average FCI (defined by the middle 40 percent) increases modestly over the horizon. We find similar patterns for the panel of EME countries; differences in the declines in GaR when there are initial credit boom conditions are significant, but the increase is downside risks are not as substantial as for the AE countries. The stronger intertemporal GaR tradeoff results for the AEs likely reflect the more significant role for financial markets and the much longer sample period over which we can estimate the model, but differences for the EMEs also are statistically significant.

Another key result is that greater downside risks to growth are not counterbalanced by higher expected growth. While additional growth from high FCI and high credit growth relative to average initial FCI is substantial in the near term, about 2 percentage points for AEs and 3 percentage points for EMEs, it diminishes moderately over the projection horizon, even as GaR falls sharply.

Our results are robust to important alternative specifications. We obtain qualitatively similar results to the quantile estimates when we use a two-step Ordinary Least Squares (OLS) procedure to estimate the empirical model of output growth with heteroskedastic volatility. The two-step approach assumes a conditional Gaussian distribution, and that the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth. The similarity in empirical results is promising for forecasting since the two-step

procedure may be easier to incorporate into regular macroeconomic forecasting exercises. We find an intertemporal GaR tradeoff for AEs when we exclude the Global Financial Crisis (GFC) in 2008 to 2009, though estimates of GaR are not as low once this episode of large negative growth is excluded and the tradeoff is less steep. Finally, results from applying this model to only the United States are similar to results from Adrian et al, (2018), suggesting the estimations are robust to some different estimates of FCI and model specification.

The empirical results in this paper have important implications for macroeconomic models and are relevant to policymaking. We document that the forecasted growth distribution changes with financial conditions, a clear violation of a common assumption when estimating macrofinancial models that volatility is independent of growth. Dynamic stochastic general equilibrium models and other models used for policymaking tend to focus on impulse response functions that depict conditional growth and, for computation reasons, assume that the mean and variance are independent. However, our results indicate that certainty equivalence is severely violated. Moreover, the covariation of conditional first and higher moments are present at horizons out to 12 quarters. Hence, these results suggest that empirical models of macrofinancial linkages should explore methods to incorporate the endogeneity of first and higher-order moments, and the implications that endogeneity may have for projections.

Although these results are not treatment effects, the intertemporal tradeoff illustrated by the term structure of GaR could have implications for policy. A structural model is needed to evaluate how macroprudential policies could be used to affect GaR. In aspiration, macroprudential policies could aim to tighten financial conditions when conditional expected growth and GaR are relatively high in order to reduce endogenous risk-taking, and reduce the future risks of bank failure and negative spillovers for the economy. The estimated term structure of GaR conditional on loose versus average initial financial conditions supports the intuition of a tradeoff between building greater resilience in normal times in order to reduce downside risks in stress periods (see Adrian and Liang, 2018). Monetary policy also faces tradeoffs between lower risks to growth in the near term and greater risks in the medium term arising from macrofinancial linkages.

A related important benefit of developing a GaR measure is that financial stability risks can be expressed in a common metric that can be used by all macroeconomic policymakers. A common metric can promote greater coordination since alternative policy options can be evaluated on the same terms. It may also improve greater accountability for macroprudential policymakers by providing a metric in terms that are better understood by other policymakers.

Our paper is related to empirical studies of the effects of financial conditions on output. As mentioned, we build on Adrian, et al. (2018), who document that financial conditions can forecast downside risks to GDP growth. Other papers look at changes in risk premia and financial conditions on output. Sharp rises in excess bond premia can predict recessions,

consistent with a model of intermediary capital constraints affecting its risk-bearing capacity and thus risk premia (Gilchrist and Zakrajsek, 2012). Also, financial frictions result in changes in borrowing being driven by changes in credit supply (see Lopez-Salido, Stein, and Zakrajsek (2017); Mian et al. (2015); and Krishnamurthy and Muir (2016)). The 12-quarter projection horizon permits us to explore an intertemporal risk-return tradeoff, as suggested by models of endogenous risk-taking (Brunnermeier and Sannikov, 2014).

The rest of this paper is organized as follows. Section II presents the stylized model of GDP growth and financial conditions, and describes the quantile regression estimation method, while Section III presents the data. Section IV defines GaR and presents estimates of the conditional GDP distribution and the importance of including FCIs. Section V provides robustness results, and highlights that a two-step OLS regression method and the quantile estimations in this paper lead to very similar tradeoff results. Section VI concludes.

II.   MODELING GROWTH-AT-RISK

We build on the Adrian, Boyarchenko, and Giannone (2018), who estimate the expected conditional GDP growth distribution for the United States. They show a tightening of financial conditions will lead to a decline in the conditional median of GDP growth and an increase in the conditional volatility, indicating greater downside risks to growth. In contrast, the upper quartiles are relatively stable to a tightening.

We expand their framework by estimating the dynamics of the GDP distribution over a projection horizon of 1 to 12 quarters using local projections estimation methods, and applying the model to panels of multiple countries. In particular, we estimate conditional distributions of GDP growth for near- and medium-term horizons, defined roughly as 1 to 4 quarters out and 5 to 12 quarters out, respectively. We expand the sample to 21 countries and allow for nonlinearities from financial vulnerabilities, approximated by high credit growth. The 21 countries are those discussed in the IMF's October 2017 Global Financial Stability Report (GFSR), and represent a set that have sufficient data for estimation.

A.   Model Estimation with Quantile Regressions

The estimates of the conditional predictive distribution for GDP growth are from panel quantile regressions. Quantile regressions allow for more general modeling of the functional form of the conditional GDP distribution. We denote $\Delta y_{i,t+h}$ as the annualized average growth rate of GDP for country i between t and $t+h$, and $x_{i,t}$ a vector of conditioning variables. The conditioning variables include FCI, GDP growth, inflation, a dummy variable for credit boom (defined by the interaction of high FCI and high credit growth), and a constant.

In a panel quantile regression of $\Delta y_{i,t+h}$ on $x_{i,t}$ the regression slope δ_α is chosen to minimize the quantile-weighted absolute value of errors:

(1) $\hat{\delta}_\alpha = \text{argmin} \sum_{t=1}^{T-h} (\alpha . 1_{\Delta y_{i,t+h} > x_{i,t}\delta} |\Delta y_{i,t+h} - x_{i,t}\delta| + (1-\alpha) . 1_{\Delta y_{i,t+h} < x_{i,t}\delta} |\Delta y_{i,t+h} - x_{i,t}\delta|)$

where $1_{(\cdot)}$ denotes the indicator function. The predicted value from that regression is the quantile of $\Delta y_{i,t+h}$ conditional on $x_{i,t}$

(2) $\widehat{Q}_{\Delta y_{i,t+h} > x_{i,t}}(\alpha) = x_{i,t}\hat{\delta}_\alpha$

We then define growth at risk (GaR), the value at risk of future GDP growth, by

(3) $\Pr\left(\Delta y_{i,t+h} \leq GaR_{i,h}(\alpha|\Omega_t)\right) = \alpha$

where $GaR_{i,h}(\alpha|\Omega_t)$ is growth at risk for country i in h quarters in the future at a α probability. Concretely, GaR is implicitly defined by the expected growth rate for a given probability α between periods t and $t+h$ given Ω_t (the information set available at t). For a low value of α, GaR will capture the expected growth at the lower end of the GDP growth distribution. That is, there is α percent probability that growth would be lower than GaR. We define GaR to be the lower 5th percentile of the GDP growth distribution. We show below estimates of the full probability density function, which illustrates that the choice of 5 percent as the cutoff is a reasonable representation of the lower tail.

We measure growth by cumulative growth between t and $t+h$ at an annual average rate to make it easier to interpret the units, rather than cumulative growth rates sometimes used in other applications of the local projection method.[3] This gives us an estimated average treatment effect of a change in FCI on the GDP growth distribution at different horizons.

To track how the conditional distribution of GDP growth evolves over time, we use Jorda's (2005) local projection method. This allows us to also explore how different states of the economy can potentially interact with FCIs in nonlinear ways in forecasting the GDP growth distribution at different time horizons,[4] while at the same time having a model that does not impose dynamic restrictions embedded in Vector Autoregression (VAR) models. Note that the approach intends to capture the forecasting effects of FCIs on GDP growth distribution, not causal effects. For simplicity, we will refer to the former as "effects" in the discussion that follows.

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[3] For example, Jorda (2005); Jorda, Schularick, and Taylor (2013).

[4] See Jorda (2005), and Stock and Watson (2018).

We estimate the model for a set of 11 AEs and a set of 10 EMEs, in panel regressions with country fixed effects. The estimated parameters on FCIs and the other independent variables represent average behavior across each set of countries at each h. Estimation of the panel quantile regressions with quantile-specific country fixed effects is feasible when the panel structure has T (the time series dimension) much larger than N (number of countries) as is the case in our forecasting application (Galvao and Montes-Rojas, 2015; and recently Cech and Barunik, 2017).[5] Inferential procedures based on bootstrap resampling within such a panel quantile set-up is considered in Galvao and Montes-Rojas (2015). These authors build on the so-called $(x,y,)$-pairs bootstrap (Freedman, 1981) under which entire rows of data (containing the dependent and conditioning variables) are sampled with replacement, and demonstrate asymptotic feasibility under various assumptions for relative sizes N and T.

Specifically, in our application we resample rows of data from the temporal dimension of each country, keeping unchanged the cross-sectional structure of the panel. To account for temporal dependence present in the data, we use a block-bootstrap strategy (Lahiri, 2003; and Kapetanios, 2008). This strategy essentially entails resampling "blocks" formed of contiguous rows of data.[6] In the analysis below, we generate bootstrap standard errors considering block widths of 4, 6, and 10 quarters but report only block widths of 4 quarters, as results are quite similar. All standard errors estimates are based on 10,000 bootstrap samples.

Below we generally report the direct estimates from the quantile regressions for the 5th, 50th, and 95th percentiles rather than estimates from a smoothed distribution. However, we also show probability density functions which we recover by mapping the quantile regression estimates into a skewed-t distribution, following Adrian et al. (2018), which allows for four time-varying moments—conditional mean, volatility, skewness, and kurtosis. To do so, we fit the skewed-t distribution developed by Azzalini and Capitaion (2003) in order to smooth the quantile function:

$$(4) \quad f(y;\mu,\sigma,\theta,\nu) = \frac{2}{\sigma} dT\left(\frac{y-\mu}{\sigma};\nu\right) T\left(\theta \frac{y-\mu}{\sigma} \sqrt{\frac{\nu+1}{\nu+\frac{y-\mu}{\sigma}}};\nu+1\right)$$

Where $dT(\cdot)$ and $T(\cdot)$ respectively denote the PDF and CDF of the skewed-t distribution. The four parameters of the distribution pin down the location μ, scale σ, fatness ν, and

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[5] The literature to date on estimating panel quantile regressions with fixed effects has focused mostly on the problem where the number of cross-sectional units N far exceeds T (Koenker, 2004). In general, estimation and associated asymptotic properties are based on restricting fixed-effects to be invariant across different quantiles (Canay, 2011).

[6] This assumption that errors are uncorrelated across countries is not unusual. It would be difficult to change in our estimations because country-level data do not have uniform availability, and we have unbalanced panels.

shape θ. We use the skewed-t distribution as it is a flexible yet parametric specification that captures the first four moments.

B.   Conditions for a Credit Boom

We incorporate the conditions for a credit boom to capture nonlinearities that could occur from a negative shock that leads to a sharp rise in the price of risk when financial vulnerabilities are high. A shock that causes a sharp increase in the price of risk may have larger consequences if they are amplified by high credit, which leads to fire sales by constrained intermediaries or to debt overhang that impedes efficient adjustments to lower prices.

This macrofinancial linkage is supported by the forecasting power of the nonfinancial credit gap for recessions in cross-country estimations (Borio and Lowe, 2002), and studies find that asset prices and credit growth are useful predictors of recessions (Schularick and Taylor, 2012) and significantly weaker economic recoveries (Jorda, Schularick, and Taylor, 2013). This linkage is also supported directly in a VAR model of the United States, where the interaction of financial conditions and the credit-to-GDP gap lead to higher volatility of GDP in the United States (Aikman, Liang, Lehnert, Modugno, 2017). Brunnermeier et al. (2017) find that the transmission of monetary policy and financial conditions are affected by credit in the United States.

To incorporate amplification channels, we define $\lambda_{i,t}$ as a dummy variable that captures the conditions for a credit boom as:

$$(5) \quad \lambda_{i,t} = \begin{cases} 1 & \text{if } \Delta\text{Credit-to-GDP and FCI each are in the top three deciles} \\ 0 & \text{else} \end{cases}$$

We use growth in the private nonfinancial credit-to-GDP ratio measured over the previous eight quarters.7 We define $\lambda_{i,t}$ when both FCI and growth are in the top three deciles of their distributions, respectively. The joint condition helps to exclude periods (a) when credit growth is high because it has just started to reverse from a bust and (b) when FCIs are still

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[7] As an alternative, we define credit boom by when the credit-to-GDP gap is positive and growth in the gap is high. The credit-to-GDP gap is a variable proposed by the Basel Committee on Banking Supervision (BCBS) as an indicator of an important financial vulnerability. When the credit gap is high and growing, looser financial conditions could set up the economy for higher volatility in the future should an adverse shock hit as highly levered borrowers suffer significant losses in collateral values. We use the BCBS, measures which apply the Hodrick-Prescott (HP) filter to nonfinancial private credit as a percent of GDP and using a smoothing coefficient of 400,000.

near recession tightness, because those conditions would not be consistent with a credit boom.[8]

Coefficients on $\lambda_{i,t}$ that are more negative in the medium term would be consistent with the effect of financial conditions through macrofinancial linkages on output growth. When there is high vulnerability, because of indebted households and businesses and a low price of risk, the combination could increase the likelihood of financial instability in the future. Highly indebted borrowers not only see their net worth fall when asset prices fall; but the decline is more likely to leave them underwater and more likely to default, generating a nonlinear effect, and also a pullback in credit. Moreover, a steep decline in net worth and a sharp decline in aggregate demand could put the economy in a liquidity trap or deflationary spiral. That situation would be seen in the data as lower downside risk in the near term but higher downside risk to GDP, i.e., lower GaR, in the medium term.

Our empirical model aims to capture the dynamics following a loosening of financial conditions, allowing for nonlinearities. To fix ideas, changes in the distribution of GDP growth are generated by changes in the price of risk, which are financial conditions. Loose financial conditions can lead to a buildup of vulnerabilities in the presence of financial frictions, such as capital requirements or VaR models of financial institutions. When asset prices rise, increased net worth can make regulatory constraints for financial intermediaries less binding, leading to a reduction in risk premia (He and Krishnamurthy, 2013) and additional risk-taking (Adrian and Shin, 2014). In addition, lower risk premia may be associated with exuberant sentiment, and suggest that periods of compressed risk premia can be expected to be followed by a reversal of valuations (Greenwood and Hanson, 2013). Lopez-Salido, Stein, and Zakrajsek (2017) show that periods of narrow risk spreads for corporate bonds and high issuance of lower-rated bonds are useful predictors of negative investor returns in the subsequent two years. The negative returns lead to lower growth, likely from a pullback in credit supply, providing empirical evidence of an intertemporal tradeoff of current loose financial conditions at some future cost to output. Loose financial conditions may also ease constraints for borrowers, who then can accumulate excess credit because they do not consider negative externalities for aggregate demand (for example, see Korinek and Simsek, 2016).

Our empirical model can be directly interpreted within the setting of Adrian and Duarte (2017), who model macrofinancial linkages in a New Keynesian setting with time-varying second moments. Expected growth corresponds to the Euler equation for risky assets, where time-varying volatility depends on the price of risk, which we measure using a financial conditions index. Time variation in the price of risk is generated by VaR constraints of financial intermediaries who intermediate credit. Hence, the conditional volatility of output

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[8] We choose the top three deciles to simplify the presentation below of the GaR term structures conditioned on initial FCIs by deciles. The results are robust to using alternatives thresholds, like top quarter or top third, but the dummy variable would then cross-over deciles and complicate the presentation.

growth is driven by the pricing of risk. Adrian and Duarte (2017) show that optimal monetary policy depends on downside risks to GDP, and consequently the conditional mean of GDP growth also depends on financial conditions.

III. DATA

We estimate the model for the 21 countries that were included in Chapter 3 of the October 2017 GFSR. Quarterly data for real GDP growth and consumer price indexes (CPIs) to measure inflation (year-to-year percent change) for the 21 countries are available from the International Financial Statistics (IFS).[9] Combined, the 21 countries represent 74 percent of world GDP in 2017. Nonfinancial credit-to-GDP ratios are from the Bank for International Settlements (BIS), and credit is to households and businesses.

We construct FCIs for each of the 21 countries, using up to 17 country-level price-based variables.[10] The FCI captures domestic and global financial price factors, such as corporate credit risk spreads, equity prices, volatility, and foreign exchange. The starting dates vary for each of the variables, and the starting dates for each of the data series and the start date for the model estimation by country is shown in Appendix I.

The FCIs are estimated based on Koop and Korobilis (2014) and build on the estimation of Primiceri's (2005) time-varying parameter vector autoregression model, a dynamic factor model of Doz, Giannone, and Reichlin (2011).[11] This approach has three benefits: (i) it controls for financial conditions of (current) macroeconomic conditions without complicating its forecasting properties for GaR; (ii) it allows for dynamic interaction between the FCIs and macroeconomic conditions, which can evolve over time; and (iii) it allows for a flexible estimation procedure that can deal with some financial indicators being available in different time periods.

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[9] Estimates of potential growth for the 21 countries are not available on a consistent basis, or for the full sample periods.

[10] The variables include: interbank spread, corporate spread, sovereign spread, term spread, equity returns, equity return volatility, change in real long-term rate, MOVE, house price returns, the percent change in the equity market capitalization of the financial sector to total market capitalization, equity trading volume, expected default frequencies for banks, market capitalization for equities, market capitalization for bonds, domestic commodity price inflation, foreign exchange moves, and VIX. These data are the same as used to construct the FCIs that were used in the October 2017 GFSR. However, we do not use the same FCIs.

[11] Compared to the FCIs in the October 2017 GFSR, we exclude two credit variables because we are interested in the interaction of FCI and credit, and we did not include a method to discriminate between periods of one-year ahead low GDP growth (below the 20th percentile of historical growth) and normal GDP growth. For robustness, we test the sensitivity of our results to the FCIs in the GFSR and results are very similar, but rely more heavily on results that are constructed in a more traditional way without credit.

The model takes the following form:

$$(6)\quad Z_t = \theta_t^y Y_t + \theta_t^f f_t + v_t$$

$$(7)\quad \begin{bmatrix} Y_t \\ f_t \end{bmatrix} = c_t + B_{t,1} \begin{bmatrix} Y_{t-1} \\ f_{t-1} \end{bmatrix} + \cdots + B_{t,p} \begin{bmatrix} Y_{t-p} \\ f_{t-p} \end{bmatrix} + \varepsilon_t$$

in which Z_t is a vector of financial variables, Y_t is a vector of macroeconomic variables of interest (in our application, real GDP growth and CPI inflation), θ_t^y are regression coefficients, θ_t^f are the factor loadings, and f_t is the latent factor, interpreted as the FCI.

Summary statistics for the panel of AEs and for the panel of EMEs are presented in Table 1. Values in the tables are averages across countries and across time, for 11 AEs and 10 EMEs. The values represent the sample estimation periods starting in 1975, 1980, or 1981 for most of the AEs, except for Spain which starts in 1992 (see Appendix I). The estimation period starts for most of the 10 EMEs in 1998, except for Brazil and Russia in 2006. The long sample period for almost all the AEs, and to a lesser extent the EMEs, allows us to capture multiple business and credit cycles, rather than only the GFC.

Table 1. Independent Variables

a. **Advanced Economies**

	Mean	Std_dev	Median	10th Percentile	90th Percentile	N
Annual growth rate	0.0221	0.0346	0.0245	-0.0161	0.0594	1576
Inflation rate	3.4636	3.3448	2.5977	0.3417	7.9407	1576
Transformed FCI	0.0181	1.0431	-0.0029	-1.1757	1.3803	1576
Credit-to-GDP	1.3443	0.4157	1.2925	0.7640	1.8770	1576
Credit-to-GDP growth	0.0055	0.0107	0.0047	-0.0066	0.0185	1576
Credit boom dummy	0.0774	0.2673	0	0	0	1576
Credit-to-GDP gap	0.0198	0.1050	0.0190	-0.1000	0.1370	1576

b. **Emerging Market Economies**

	Mean	Std_dev	Median	10th Percentile	90th Percentile	N
Annual growth rate	0.0447	0.0613	0.0476	-0.0100	0.1070	613
Inflation rate	7.1502	9.2600	4.9794	1.5814	11.1104	613
Transformed FCI	-0.0192	1.0842	-0.1160	-1.1728	1.3870	613
Credit-to-GDP	0.7324	0.4610	0.5890	0.2570	1.4800	613
Credit-to-GDP growth	0.0043	0.0144	0.0046	-0.0101	0.0190	613
Credit boom dummy	0.0799	0.2714	0	0	0	613
Credit-to-GDP gap	0.0078	0.1061	0.0230	-0.1280	0.1190	613

Source: IMF International Financial Statistics database: Bank for International Settlements; and IMF staff estimates.

Note. Table includes descriptive statistics for 11 advanced economies (AEs) and 10 emerging market economies (EMEs). The 11 AEs include Australia, Canada, France, Germany, Great Britain, Italy, Japan, Spain, Sweden, Switzerland, and the United States. The 10 EMEs include Brazil, Chile, China, India, Indonesia, Mexico, Russia, Turkey, South Africa, and South Korea. The start of the estimation period is either 1975 or 1980 for most of the AEs, and 1988 for most EMEs. Specific starting dates for each country are shown in Appendix I.

There are some important differences between the AEs and EMEs, supporting our choice to estimate separate panels. Not surprisingly, average growth is lower in the AEs than in the EMEs, about half as fast. Average annual growth is 2.2 percent in AEs, and 4.5 percent in EMEs. Inflation in the AEs is much lower than in the EMEs, 3.5 percent and 7.2 percent annual rate.

In addition, AEs have higher credit-to-GDP ratios, quarterly growth rates, and higher credit-to-GDP gaps. Periods when the credit boom λ is equal to 1, when credit growth and FCI are each in the top three deciles of their distributions, represent about 8 percent of the AE and EME samples. We then can observe how a configuration of high FCIs with positive credit growth will evolve and determine growth over horizons up to three years later.

Regression estimates (not shown) show that FCIs are have significant positive coefficients for credit-to-GDP growth and credit-to-GDP gap multiple quarters ahead, suggesting credit responds to FCI with a lag. Data indicate that the coefficient estimates do not reflect a single episode of loose financial conditions and a credit boom and bust, but reflect a number of different business and credit cycles.

IV. EMPIRICAL RESULTS

In this section, we show GaR estimates from quantile estimations along a number of important dimensions where GaR is calculated for each country-time observation for h=1 to 12, based on initial FCI, inflation, growth, and λ. First, we show the time series of GaR averaged across countries at a given projection horizon and show there is greater variance in downside than in upside risks. Second, we show the probability density functions of expected growth for the country panels at two projection horizons, which illustrate the increase in the negative skew between the short term and the medium term when initial financial conditions are loose and credit is high. Third, we show the term structure of GaR based on groups defined by the level of the initial financial conditions, and that the increase in downside risks in the medium term is greater when initial financial conditions are loose than when they are moderate; this comparison provides an estimate of the intertemporal risk tradeoff relative to typical conditions. Finally, we show the term structures of both median growth and GaR by initial FCI groups, to illustrate a potential intertemporal risk-return tradeoff from initial loose financial conditions. The estimates show that while initial loose FCI and high credit project higher expected growth and GaR in the near-term, the growth differential declines modestly while the GaR decline is substantial, suggesting sharp increases in downside risks without the benefit of higher growth.
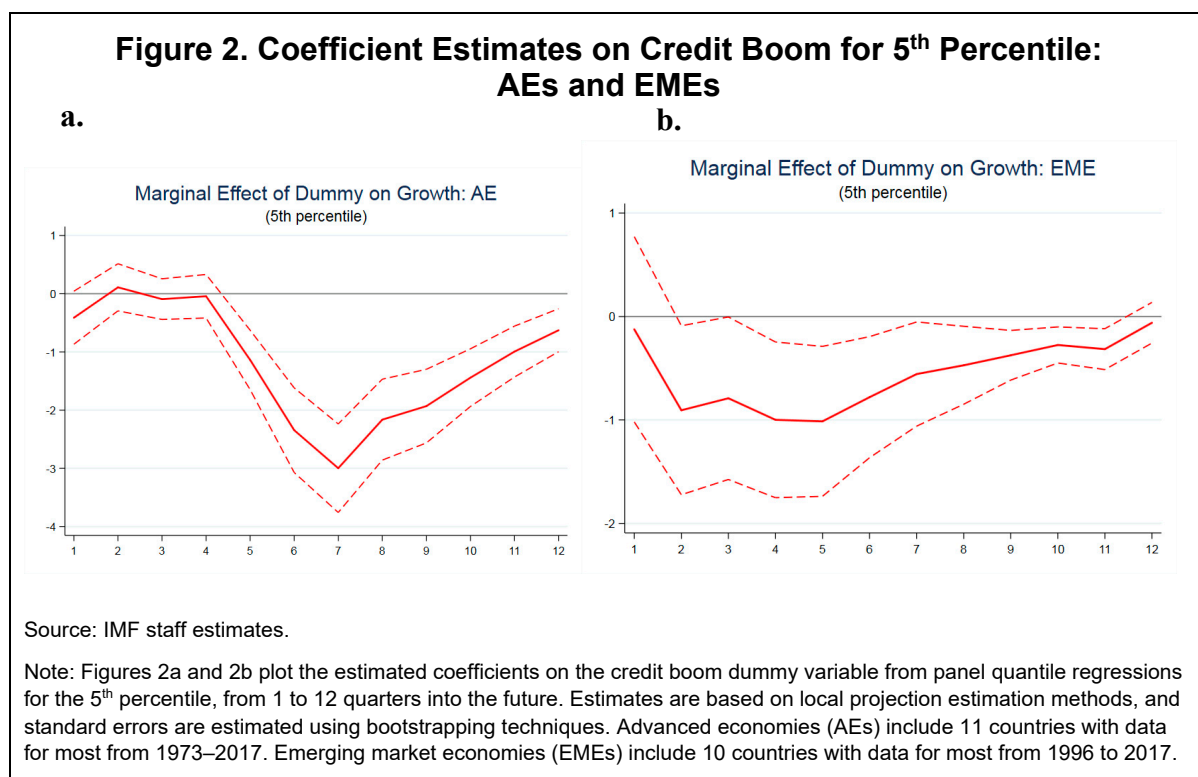
A. Estimated FCI Coefficients with Interaction

Figures 1a and 1b shown above are the estimated coefficients on FCI, where higher FCI represents looser financial conditions (lower price of risk). As discussed above, coefficients for GaR are positive in the near term, and become negative in quarters further out. They

provide strong empirical support for an intertemporal tradeoff of loose financial conditions and low downside risk at short horizons, which set the stage for a deterioration in performance three years later.

Figures 2a and 2b show the coefficients on λ for the 5th percentile quantile regressions over the projection horizons, for AEs and EMEs, respectively. The coefficients on λ for the AEs are highly negative starting at $h=5$ and stay negative through the rest of the projection horizon, though the size of the effect moderates in quarters further out. The coefficient estimates indicate the marginal effect of initial credit boom substantially increase downside risk (reduce GaR) within the second year.

For EMEs, the estimated coefficients on λ also are negative; but its effects on GaR are more modest and occur earlier than for AEs, within two to six quarters ahead. Below we use these marginal effects to calculate the conditional GaR (using all conditioning variables) to evaluate the effects of both high FCI and high credit growth.

Figure 2. Coefficient Estimates on Credit Boom for 5th Percentile: AEs and EMEs

a.

b.

Source: IMF staff estimates.

Note: Figures 2a and 2b plot the estimated coefficients on the credit boom dummy variable from panel quantile regressions for the 5th percentile, from 1 to 12 quarters into the future. Estimates are based on local projection estimation methods, and standard errors are estimated using bootstrapping techniques. Advanced economies (AEs) include 11 countries with data for most from 1973–2017. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2017.

The significant coefficients for λ are consistent with macrofinancial linkages that can lead to variation in the distribution of expected growth. Otherwise, it could just be that financial conditions are forward-looking and respond quickly to adverse events, whereas it takes time for such events to work their way through real economic activity. If the link from financial conditions to growth were just a common shock, we would not expect larger costs because growth in credit or the credit gap is high. The higher costs in the medium term estimated for

high credit growth periods is consistent with an endogenous risk-taking channel helping to explain the reduction in volatility in the near term, which allows more risk-taking, and leads to higher volatility in the medium term.

B. Time Series of Average GaR

Figures 3a and 3b show the time series of average GaR estimates (averaged across countries), at the projection horizon of four quarters ($h=4$) for AEs and for EMEs. Also plotted are the conditional median and the 95th percentile, as well as realized growth (shifted forward by four quarters). The time series reveals that lower projected median growth is associated with lower GaR, consistent with conditional growth and volatility being negatively correlated. In sharp contrast, there is very little variability at the 95th percentile, suggesting greater variability for downside risk than upside risk.
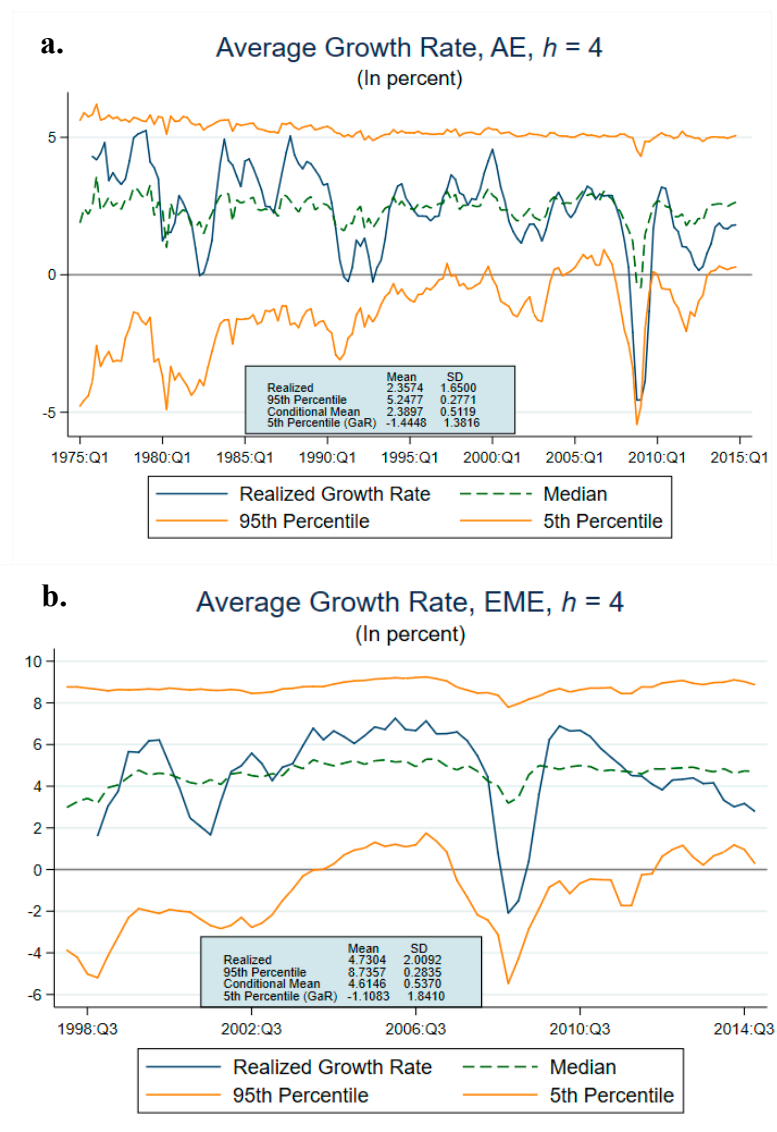
In particular, the mean GaR for AEs over the sample period is -1.4 percent, with a standard deviation of 1.4 (Figure 3a). In contrast, the standard deviation of the 95th percentile is lower at 0.28, even though the mean 95th percentile is much higher, at 5.2 percent. Basically, the conditional 95th percentile show little variation, while GaR is highly variable. Similarly, the mean GaR for EMEs is -1.1 percent with a standard deviation of 1.84 percent, while the standard deviation of the 95th percentile is 0.28 percent (Figure 3b). The downside risk as represented by GaR shows much greater variability than upside risk as the conditional mean changes over time.

Moreover, the results expand on Adrian et al. (2018) by demonstrating the results for panels of AEs and EMEs. The results we obtain based on the panel of AEs is quite similar to those for the United States only. For comparison, we present below the time series results for the U.S. only, as a comparison to Adrian et al. (2018) (see Section V.B, Figure 12).

C. Probability Density Functions of Expected Growth and GaR

In this section, we show the entire probability density function derived by fitting the quantile regression estimates to a skewed-*t* distribution, as described above by equation (4). The growth distributions can be used to illustrate the conditional expected GaR as well as the tails, and the dynamics of the term structure. We plot the expected growth distribution conditional on high FCI (top 1 percent) and credit boom at two points on the term structure, at $h=4$ and $h=10$ quarters. For AEs, this conditional growth distribution for $h=4$ has very little mass in the left tail, while the distribution at $h=10$ has a lot of its mass in the left tail (Figure 4a). The distribution shifts and shows downside risks have increased considerably from $h=4$ to $h=10$ for these initial conditions.

Figure 3. Average Growth-at-Risk, Median, and 95th Percentile at *h*=4: AEs and EMEs

a. Average Growth Rate, AE, *h* = 4
(In percent)

	Mean	SD
Realized	2.3574	1.6500
95th Percentile	5.2477	0.2771
Conditional Mean	2.3897	0.5119
5th Percentile (GaR)	-1.4448	1.3816

— Realized Growth Rate   - - - - Median
— 95th Percentile   — 5th Percentile

b. Average Growth Rate, EME, *h* = 4
(In percent)

	Mean	SD
Realized	4.7304	2.0092
95th Percentile	8.7357	0.2835
Conditional Mean	4.6146	0.5370
5th Percentile (GaR)	-1.1083	1.8410

— Realized Growth Rate   - - - - Median
— 95th Percentile   — 5th Percentile

Source: IMF staff estimates.

Note. Figures plot the cross-country averages of conditional mean growth, growth at risk (5th percentile), and 95th percentile, derived via estimation of the distribution of growth from quantile regressions. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2017.

In contrast, for high FCI but without a credit boom, the shift in the distribution between *h*=4 and *h*=10 is less pronounced (Figure 4b). In Appendix II, we show the shifts correspond to a sizable increase in the probability of GaR falling below zero at each projection horizon for *h*=1 to 12 implied by the distributions. As shown, this probability is negligible in the near-term but rises significantly to almost 20 percent in the medium-term for high FCI and a credit boom. Without a credit boom, the probability of negative growth rises more modestly from zero to about 9 percent for high FCI.

For EMEs, the distributions at *h*=4 are fatter than for the AEs, but changes between *h*=4 and *h*=10 exhibit a similar pattern of shifting to the left. The conditional growth distribution at *h*=4 has a smaller left tail and a higher mean than the distribution at *h*=10, both when there is a credit boom and when there is not (Figures 4c and 4d). The risk of the probability of GaR for EMEs falling to below 2 percent is about 0 percent in the near term but increases to 35 percent in the medium term with initial credit boom conditions, and to 30 percent when initial FCI was high but credit growth was not (Appendix II).

Figure 4. Probability Density Functions of Conditional GDP Growth: AEs and EMEs
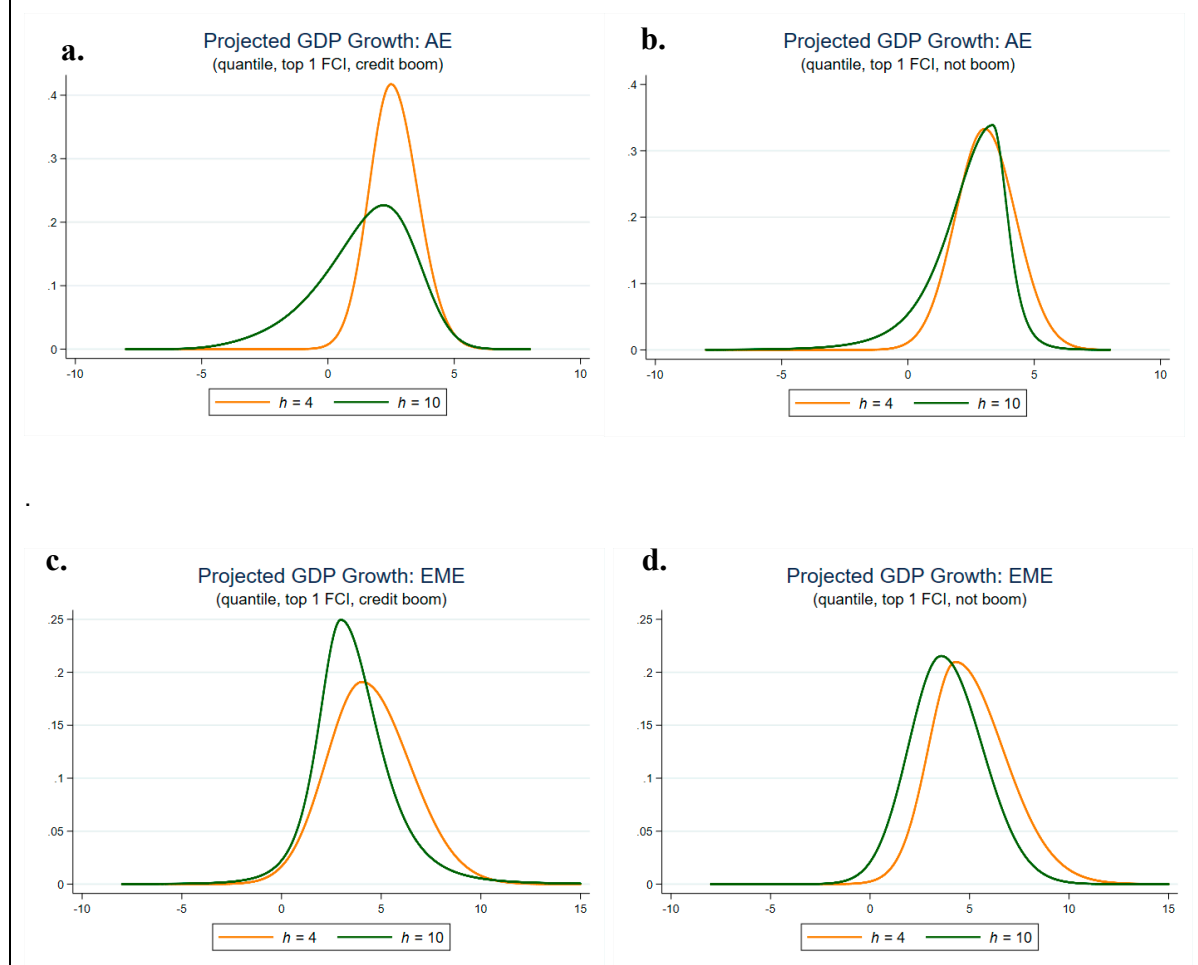
Source: IMF staff estimates.

Note. Probability density functions are estimated using panel quantile regression methods and fitted to a skewed-*t* distribution. Advanced economies (AEs) include 11 countries most with data from 1973 to 2017. Emerging market economies (EMEs) include 10 countries most with data from 1996 to 2017.

D.   Term Structures of GaR by Initial FCI Groups

The probability density functions shown in Figure 4 provide the entire smoothed distribution for a given FCI, credit boom indicator, and projection horizon. Next, we look more closely at risks in the lower tail, specifically the 5th percentile, although the density functions indicate that results would be robust to other percentiles in the near vicinity, such as the 2½, 7½, or 10th percentiles. For the 5th percentile, we can show the term structure of GaR based on different initial FCI decile groups to evaluate if loose FCI is more likely to have both lower risk in the near term and higher risk later. We show GaR term structure estimates based on initial average FCI values for four groups: in the top 1 percent (very loose financial conditions); top decile (loose financial conditions); bottom decile (very tight financial conditions); and middle 40 percent, and by whether λ, credit boom, is equal to zero or one.

When initial FCIs are in the top decile or higher, the estimated GaRs are initially high but fall over most of the projection horizon, indicating downside risks increase in the medium term (Figures 5a and 5b); the downward slope is much sharper when there is also a credit boom. These term structures indicate an intertemporal tradeoff for risk. For AEs, GaR is about 1 percent in the near term for very loose FCIs (Top 1) and credit boom, but it then falls significantly over the projection horizon to less than -2.0 percent at around h=8, a swing of more than 3 percent; the decline in GaR for FCI in the top decile (Top 10) is about 2.5 percent. We use the four middle deciles (labeled Mid 40) of initial FCI values to represent "typical" moderate conditions, to approximate for expected growth and downside risk when FCIs are neither high nor low. Estimated GaRs for initial FCI in the mid-range (Mid 40) rise initially and then level out at about -0.5 percent in the medium term. That is, the term structure for the moderate FCI group slopes upward rather than downward, as moderate FCIs do not increase downside risks to growth in the medium term.[12]

To compare the differences in the GaR term structures, we calculate the differences between the Top 1 percent and the Mid 40 FCI groups, and we test for the statistical difference between the term structures by calculating standard errors by bootstrapping the differences in GaRs at each horizon h. The differences in the term structures between the average FCI in the Top 1 with a credit boom and Mid 40 are positive and statistically significant in the near term, and turn negative and statistically significant in the medium term (Figure 5c), indicating that the lower downside risks in the near term from the loose FCI reverse and become larger in quarters further out. The difference in term structures for Top 1 and Mid 40 for no credit boom is also positive and significant in the short term, and falls over the projection horizon; but the magnitude of the decline is smaller (Figure 5d). Under credit boom conditions, the difference in GaR is about 2 percentage points lower—at about h =8 to 10 than when no credit boom—suggesting credit growth plays an important role in

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[12] Note that because credit boom was defined by high credit growth and FCI in the top three deciles, the estimated term structures of GaR for the Mid 40 do not differ for credit boom and not credit boom.

amplifying changes in financial conditions, consistent with theories of macrofinancial linkages.

Figure 5. Term Structures of GaR by Initial FCI Groups and Differences: AEs
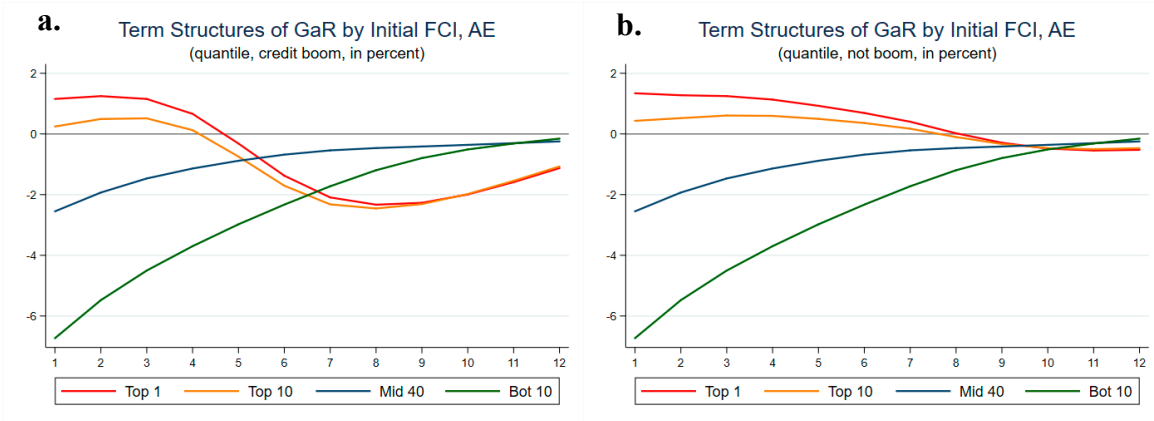
Source: IMF staff estimates.

Note. Figures plot the GaR (expected growth at the 5th percentile) at an annual rate. The GaR projections are grouped on initial FCI levels by the Top 1 percent, top decile, bottom decile, and a middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on quantile regressions with local projection estimation methods, and standard errors are from bootstrapping techniques. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017.

Source: IMF staff estimates.

Note. Figures plot the differences in the GaR term structures of the Top 1 percent minus the Mid 40. Standard errors are from bootstrapping techniques on the differences. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017.

For EMEs, the GaR term structures are not as steeply downward-sloped as for the AEs for the initial high FCI groups (Figures 6a and 6b). However, the differences in the term

structures for average FCI values in the Top 1 and Mid 40, for both credit boom and not, are significant and statistically different (Figures 6c and 6c). This difference reflects that loose financial conditions relative to moderate significantly mitigate near-term downside risks, and while the effects reverse only modestly over time, more moderate FCI initially would have led to greater reduction in downside risks. In addition, as shown previously in Figure 2, the effects of a credit boom on the 5th percentile of expected growth are most evident at near-term horizons, $h=2$ to $h=5$, rather than in the medium-term as is the case for the AEs.

Returning to the term structures in Figure 5a and Figure 6a, the estimates also show that the worst outcomes in the short run are when FCIs are initially extremely tight, in the lowest decile ("Bot 10"). GaR for AEs and EMEs are very low in the short run (-6 percent and -10 percent, respectively), suggesting the economy is in a deep recession or a financial crisis. However, these effects dissipate over time and, for the AEs, converge in the medium term to the same GaR as for initial moderate financial conditions. We view very low FCIs as reflecting the realization of a negative shock, not a deliberate policy choice. What determines initial financial conditions is outside this empirical model; but a number of models with endogenous risk-taking behavior would predict that high FCIs that also lead to greater financial vulnerabilities set the stage for sharper falls in FCIs when there is a negative shock (Brunnermeier and Pedersen (2009); Brunnermeier and Sannikov (2014); and Adrian and Shin (2014)),or sharp declines in FCI may reflect sharp sentiment reversals that are triggers that interact with vulnerabilities and lead to recessions and credit busts (Minsky, 1977). We leave to future work an approach to estimating the term structures of the joint distribution between FCIs and GDP growth.

E. Term Structures of Expected Median and GaR by Initial FCI Groups

So far, we have focused on GaR, the lower 5th percentile of the expected growth distribution. But a drop in the 5th percentile could also be accompanied by higher expected growth (the 50th percentile), in which case an alternative interpretation of higher growth and higher risk is possible. In this section, we evaluate the projected additional expected growth and reduction in downside risks from initial loose financial conditions relative to typical financial conditions over the term structure. We find that the projected additional expected growth falls modestly over the projection horizon. That is, conditioning on loose FCI and credit boom relative to average FCI, the intertemporal risk tradeoff—less risk now at the cost of more risk later—is not mitigated by higher expected growth later.

To see this tradeoff, we plot the projected median and GaR term structures for the Top 10 and Mid 40 FCI groups, for high credit and low credit, for AEs and EMEs (Figure 7). While the median and GaR term structure projections vary across the AE and EME panels, there are some important common features: First, median growth is higher in the near term for FCI in the Top 10 than for Mid 40 in all cases, and the gap shrinks over time, mostly as the projected median growth for Top 10 FCI falls. That is, the marginal contribution to growth from high FCI diminishes somewhat over the projection horizon. Second, GaR is higher

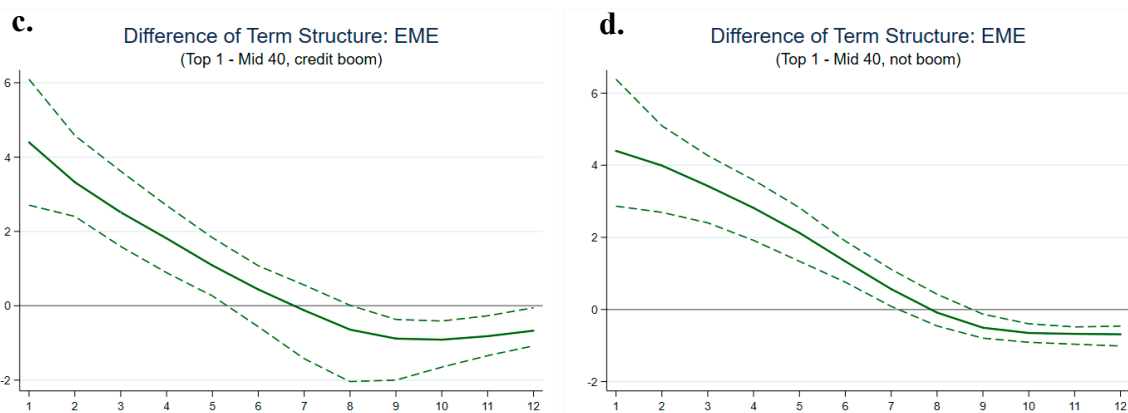(downside risk is lower) for top decile FCI than for Mid 40 FCI in the near term in all cases; then, for AEs, it falls over the projection horizon. The reversal is substantial for credit boom conditions. Note also that the projected median growth for typical Mid 40 FCI is flat over the projection horizon, at slightly under 2 percent for AEs and 3 percent for EMEs, suggesting this FCI group is a reasonable characterization of neutral financial conditions, and that neutral financial conditions are consistent with steady growth and diminishing downside risks.

Figure 6. Term Structures of GaR by Initial FCI Groups and Differences: EMEs
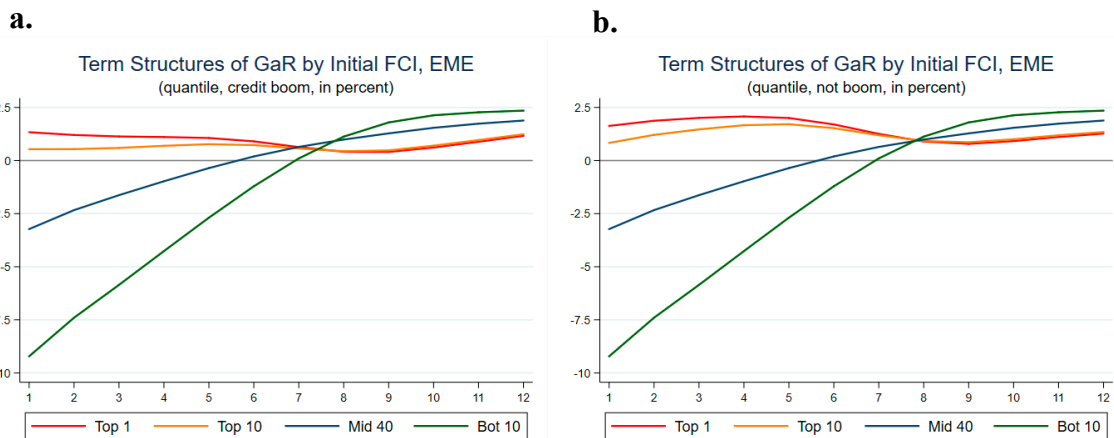
a.

Term Structures of GaR by Initial FCI, EME
(quantile, credit boom, in percent)

b.

Term Structures of GaR by Initial FCI, EME
(quantile, not boom, in percent)

Source: IMF staff estimates.

Note. Figures plot the GaR (expected growth at the 5th percentile) at an annual rate. The GaR projections are grouped on initial FCI levels by the Top 1 percent, top decile, bottom decile, and a middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on quantile regressions with local projection estimation methods, and standard errors are from bootstrapping techniques. EMEs include 10 countries with data for most from 1996 to 2017.

c.

Difference of Term Structure: EME
(Top 1 - Mid 40, credit boom)

d.

Difference of Term Structure: EME
(Top 1 - Mid 40, not boom)

Source: IMF staff estimates.

Note. Figures plot the differences in the GaR term structures of the Top 1 percent minus the Mid 40. Standard errors are from bootstrapping techniques on the differences. EMEs include 10 countries with data for most from 1996 to 2017.

Figure 7. Term Structures by Initial FCI Groups—Conditional Median and GaR: AEs and EMEs

a. Term Structures by Initial FCI: Median and GaR
(AE, credit boom, in percent)

b. Term Structures by Initial FCI: Median and GaR
(AE, not boom, in percent)

c. Term Structures by Initial FCI: Median and GaR
(EME, credit boom, in percent)

d. Term Structures by Initial FCI: Median and GaR
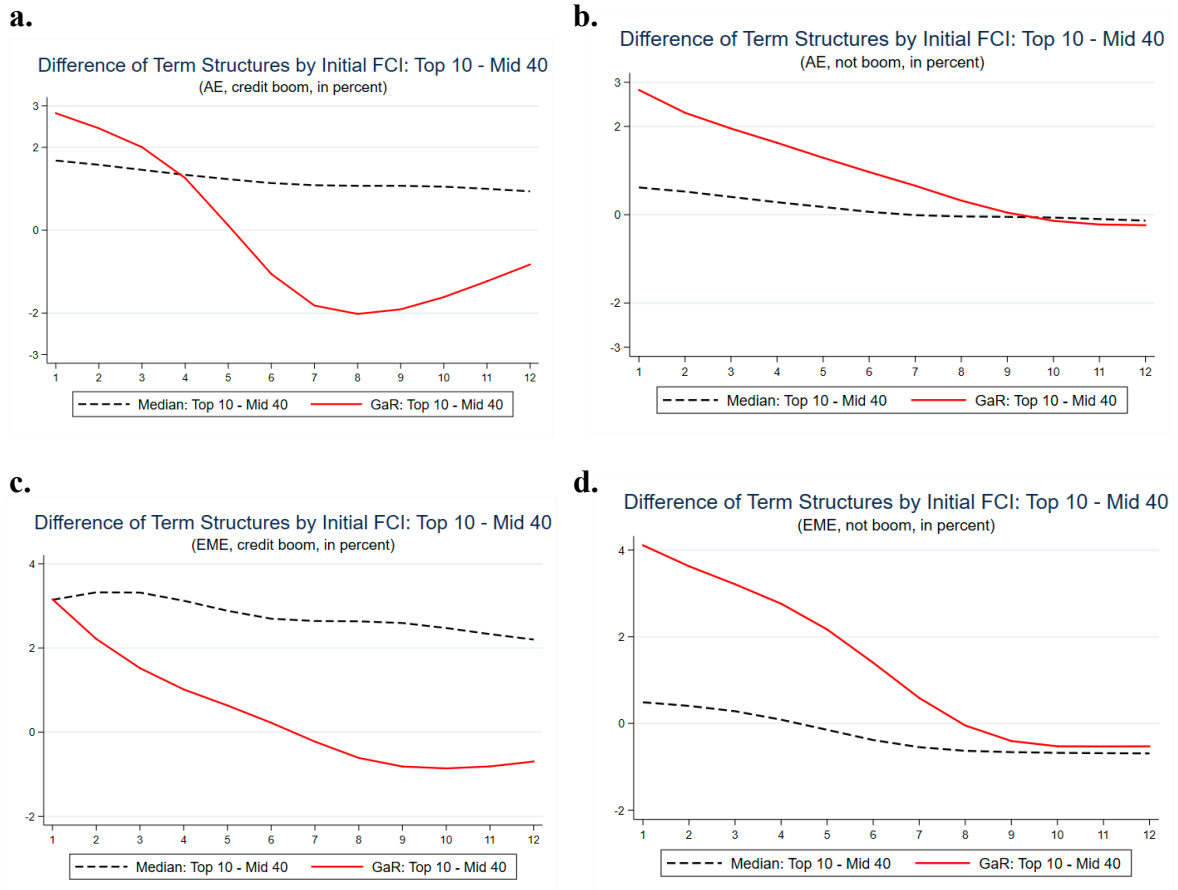(EME, not boom, in percent)
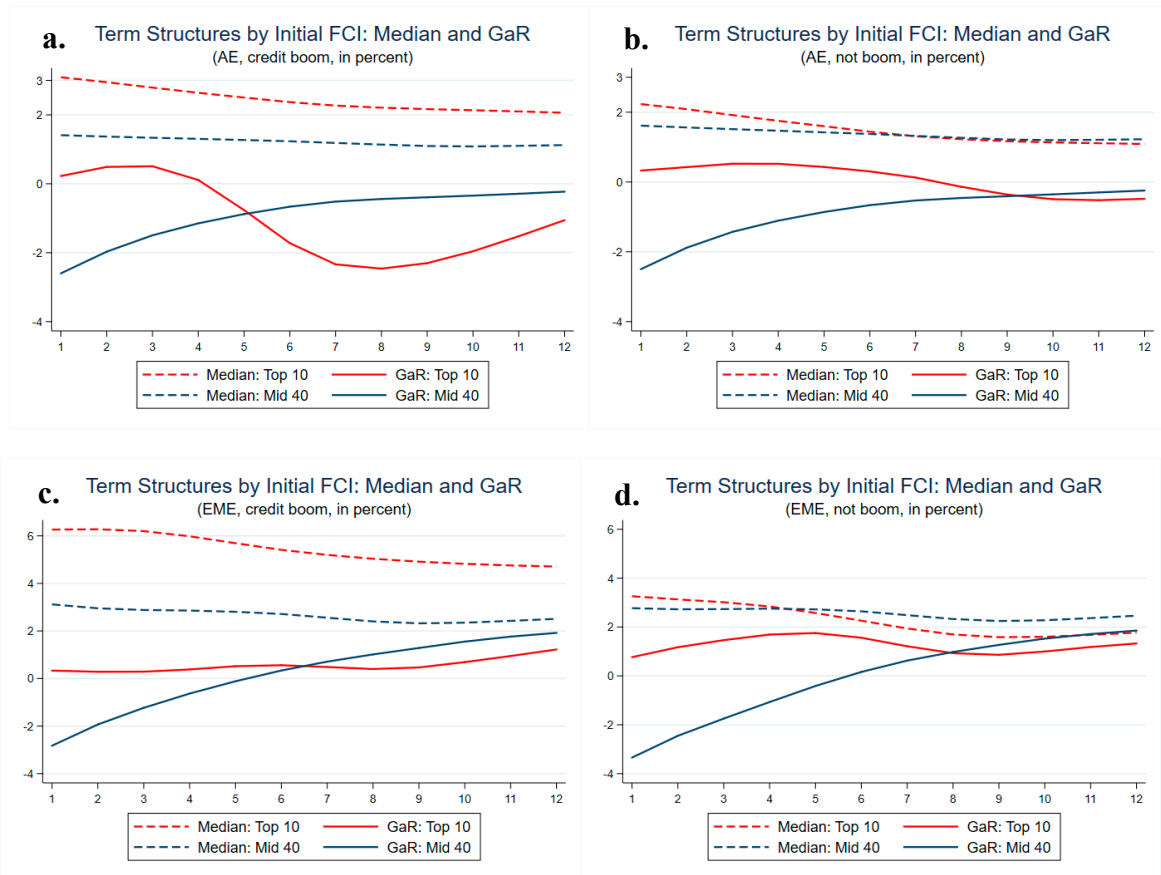
Source: IMF staff estimates.

Note: Figures plot expected median and GaR (expected growth at the 5th percentile) at an annual rate for initial FCI levels top decile (Top 10) and middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on quantile regressions with local projection estimation methods, and standard errors are from bootstrapping techniques. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017. EMEs include 10 countries with data for most from 1996 to 2017.

Figure 8 plots the information in Figure 7 as differences in the term structures between the top decile and the neutral case for the projected medians and GaR. The differences make it more evident that the decline in GaR is much steeper than the decline in the median growth in all four cases. For AEs with a credit boom, the decline in GaR is much sharper than the decline in expected median growth. This configuration illustrates the costs of a credit boom. In contrast, when there is not a credit boom, the decline in GaR—the amplification effect—is less sharp, and the decline in the marginal boost to growth is very modest. This configuration illustrates a situation of slower growth but also lower downside risks. For EMEs in credit boom conditions, while GaR also declines sharply over the projection horizon, the magnitude of the declines are less sharp than in the AEs, indicating the magnitude of a risk tradeoff is quite different. Moreover, the greater differential for higher expected growth between credit

boom and not credit boom suggests high credit has greater benefits to growth in the near term for the EMEs than for the AEs.

Figure 8. Difference of Term Structures by Initial FCI Groups—Top 10 Minus Mid 40: AEs and EMEs

a.

Difference of Term Structures by Initial FCI: Top 10 - Mid 40
(AE, credit boom, in percent)

- - - - Median: Top 10 - Mid 40 ——— GaR: Top 10 - Mid 40

b.

Difference of Term Structures by Initial FCI: Top 10 - Mid 40
(AE, not boom, in percent)

- - - - Median: Top 10 - Mid 40 ——— GaR: Top 10 - Mid 40

c.

Difference of Term Structures by Initial FCI: Top 10 - Mid 40
(EME, credit boom, in percent)

- - - - Median: Top 10 - Mid 40 ——— GaR: Top 10 - Mid 40

d.

Difference of Term Structures by Initial FCI: Top 10 - Mid 40
(EME, not boom, in percent)

- - - - Median: Top 10 - Mid 40 ——— GaR: Top 10 - Mid 40

Source: IMF staff estimates.

Note: Figures plot the differences in the expected median and GaR (expected growth at the 5th percentile) at an annual rate for initial FCI levels top decile (Top 10) and middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on quantile regressions with local projection estimation methods, and standard errors are from bootstrapping techniques. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017. EMEs include 10 countries with data for most from 1996 to 2017.

F.   Interpreting the Intertemporal Risk-Return Tradeoff

We have shown with GaR and the probability density functions that the differences in term structures between high and moderate initial FCI groups are statistically different. While we do not model the determination of FCIs, and our estimates are not treatment effects, the increased downside risks in the medium term associated with looser financial conditions

(lower price of risk) suggests that policymakers might want to incorporate tradeoffs when evaluating future downside risks.

An important consideration, conditional on this intertemporal tradeoff, is whether the higher future downside risks are substantial enough to want to forego lower downside risks in the near term. We have not specified a policymaker's welfare function, as our goal in this paper is to test empirically for whether a tradeoff exists. A welfare function that would apply a simple time discount factor might not find the future higher downside risks to be great enough to offset the near-term benefits of lower downside risks since the term structures suggest the positive differences in the short-run are greater in magnitude than the negative differences in quarters further out.

But a more economically significant tradeoff might exist if the welfare function were to incorporate that the costs of large downside risks are high and the costs increase nonlinearly. For example, a reduction in GaR from 0 percent to -1 percent has greater welfare costs than a similar-sized reduction in GaR from 2 percent to 1 percent since the costs of a recession in the latter case is still negligible, and the costs of 0 percent to -1 percent are less than the welfare costs of -1 percent to -2 percent.[13] Our evidence suggests that initial very loose FCI and high credit relative to average FCI in AEs indicate sharp declines in GaR, a marginal boost to expected growth that diminishes somewhat over the term structure, and an increase in the probability of a recession over the projection horizon.

Another case where higher downside risks in the future might be more costly than implied by a time discount factor is if policymakers have limited tools to remedy a recession if one were to occur. This could be the case if monetary policy rates are near the zero lower bound, there are operational or political constraints to quantitative easing, or fiscal debt is already at unstainable levels.

V.   ROBUSTNESS

We provide a number of robustness checks to our estimations, starting with an alternative two-step OLS estimation of mean and variance rather than quantile estimates, and find very similar results. We then report some results excluding the GFC peak years of 2006 to 2009, and find that the intertemporal risk tradeoffs remain, although GaR estimates are not as low as when we include the more extreme negative outcomes. We also report results specifically for the United States, and show results are similar to Adrian et al. (2018) and robust to a slightly different empirical model and different FCIs.

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[13] Wolfers (2003) finds that greater macroeconomic volatility and higher unemployment has an adverse impact on different social welfare metrics. The costs of recessions in which there are large-scale job losses and financial distress are viewed to be costly and associated with significant waste because separations may destroy contractually fragile relationships (Hall, 1995; Ramey and Watson, 1997).

A. Growth at Risk in a Heteroskedastic Variance Model—Two-Step OLS Regressions

In this section, we compare the results from the panel quantile regressions to a two-step OLS panel estimation method. We show below that the two-step procedure for estimating the mean and variance assuming an unconditional Gaussian distribution can capture the dynamics of the term structure of GaR, although the assumptions do not allow the GaR estimates to be as negative as estimated with quantiles.

For the two-step OLS estimation, we use the same empirical model of GDP growth, and estimate the mean and variance of output growth for different projection horizons h (where h goes from 1 to 12 quarters) as a function of regressors at time t. The model is described by the following two equations:

$$(8) \quad \Delta y_{i,t+h} = \gamma_0^{(h)} + \gamma_1^{(h)} f_{i,t} + \gamma_2^{(h)} \Delta y_{i,t} + \gamma_3^{(h)} \pi_{i,t} + \gamma_4^{(h)} \lambda_{i.t} + \varepsilon_{i,t} \quad h = 1, \dots, 12$$

$$(9) \quad \ln \hat{\varepsilon}_{i,t+h}^2 = \beta_0^{(h)} + \beta_1^{(h)} f_{i,t} + \beta_2^{(h)} \pi_{i,t} + \beta_3^{(h)} \lambda_{i,t} + v_{i,t} \quad h = 1, \dots, 12$$

where $\Delta y_{i,t+h}$ is the average GDP growth rate between quarter t and $t+h$ for country i, $f_{i,t}$ is the FCI, $\pi_{i,t}$ is the inflation rate, $\lambda_{i,t}$ is the same time varying dummy variable that measures the stance of the credit cycle as above, $\varepsilon_{i,t}$ is an heteroskedastic error term that affects the volatility of GDP growth, and $v_{i,t}$ is an independently identically distributed (i.i.d.) Gaussian error term. This model can be thought of as a panel extension of an autoregressive conditional heteroskedasticity (ARCH) model, in which the heteroskedasticity is modeled with an exponential function of the regressors.

We first estimate the relationship between the change in output on financial conditions and the other variables, including country fixed effects, equation (8). We then use the residuals from the estimated equation and regress $\ln \hat{\varepsilon}_{i,t+h}^2$ onto the right-hand side variables of equation (9).[14] This two-equation empirical model assumes a conditionally Gaussian distribution with heteroskedasticity that depends on financial conditions, which yields a tractable yet rich model where the unconditional distribution of GDP growth is skewed as the conditional mean and the conditional volatility are negatively correlated.[15] Standard errors are computed using Newey West standard errors that correct for the autocorrelation in the

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[14] Note that the estimated residuals $\hat{\varepsilon}_{i,t}$ are not a "generated regressor" and thus they can be used directly in the second stage equation (see Pagan, 1984).

[15] Given the assumption of a conditional Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth.

error term generated by the local projection method (see Jorda (2005), and Ramey (2016) for a discussion of standard errors for local projection regressions).

GaR, the expected conditional growth in the lower (left) tail of GDP growth distribution, is computed as:[16]

$$(10) \quad GaR_{i,t+h}(\alpha) = E\big(\Delta y_{i,t+h}|\Omega_t\big) + N^{-1}(\alpha)Vol\big(\Delta y_{i,t+h}|\Omega_t\big)$$
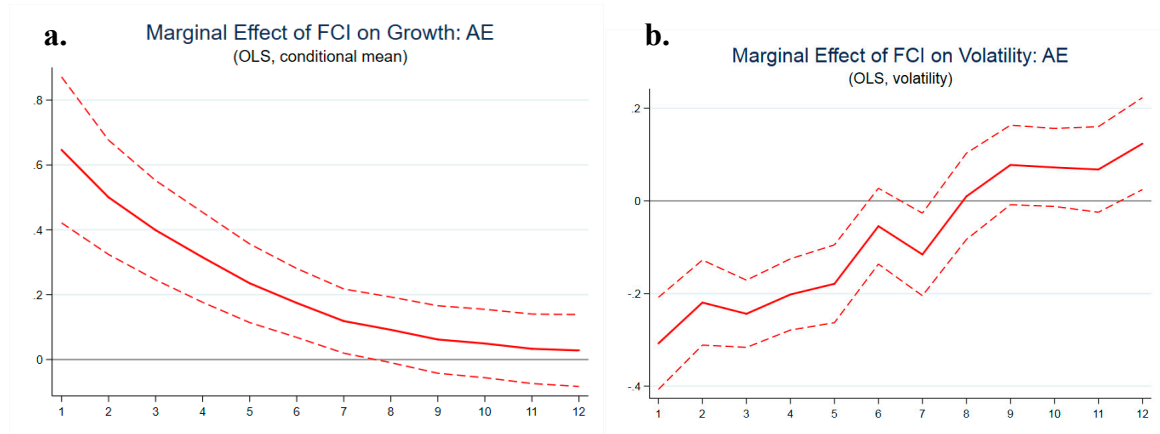
where $GaR_{i,t+h}(\alpha)$ is growth at risk for country i in $t+h$ quarters in the future at an α probability; $E\big(\Delta y_{i,t+h}|\Omega_t\big)$ is the expected mean growth for period $t+h$ given the information set Ω_t available at t obtained by fitting equation (8); $Vol\big(\Delta y_{i,t+h}|\Omega_t\big)$ is the expected volatility at period $t+h$, which is equal to the squared root of the exponent of the fitted value for equation (9); $N^{-1}(\alpha)$ denotes the inverse standard normal cumulative probability function at a probability level α. As above, α is fixed at 5 percent, thus capturing the left tail of GDP growth in the 5th percentile of its conditional distribution.

Estimated coefficients on FCI for expected growth and volatility support the results from the quantile regressions. For AEs, the coefficients for growth are positive in the near term, but diminish over the projection horizon (Figure 9a). At the same time, the coefficients for volatility are negative in the near term and increase over the projection horizon (Figure 9b). That is, FCI tends to increase growth and reduce volatility in the near term, but the effects on growth dissipate while volatility increases in the medium term. The same pattern holds for EME growth and volatility coefficients (Figures 9c and 9d). These results suggest an intertemporal tradeoff of higher growth in the near term, and lower growth with higher downside risks in the medium term.

We derive the GaR term structures and condition on initial FCIs and credit boom, based on the two-step OLS estimates. Figure 10 is the counterpart to Figures 5 and 6, which were based on the quantile estimations. The term structures of the GaR from the two-step estimation procedure with assumed Gaussian distributions have very similar shapes to the GaR from the quantile estimations, indicating qualitative results are robust to alternative estimation methods. The GaR estimates are higher with the two-step procedure because of the stronger distributional assumptions under the two-step method. The quantile approach is less constraining on the variance and GaR estimates since it is semiparametric and allows for more general assumptions about the functional form of the conditional GDP distribution. Still, the implied cross-sectional distinctions based on initial FCI from the simpler-to-implement two-step procedure are consistent with the existence of a substantial intertemporal tradeoff found with the quantile regressions.
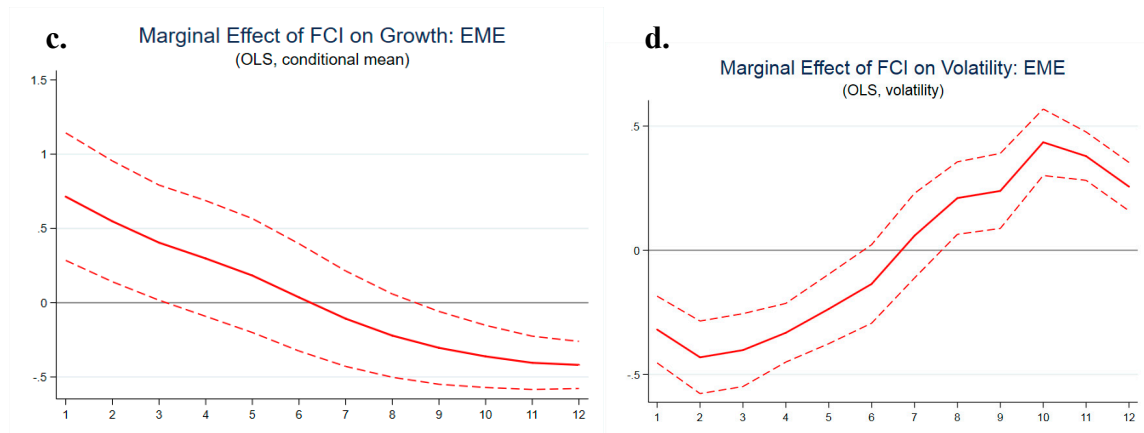
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[16] Adrian and Duarte (2017) show that for a low value of α this is a good approximation as higher-order terms go rapidly to zero.

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Figure 9. Marginal Effects of FCI on Growth and Volatility from Two-Step OLS Estimations: AEs and EMEs

a. Marginal Effect of FCI on Growth: AE
(OLS, conditional mean)

b. Marginal Effect of FCI on Volatility: AE
(OLS, volatility)

Source: IMF staff estimates.

Note. Figures plot the estimated coefficients on the financial conditions index (FCI) and its interaction with high credit growth on GDP growth and GDP volatility for projection horizons from 1 to 12 quarters. Higher FCI represents looser financial conditions. Estimates are based on two-step OLS estimations, and standard errors are robust to heteroskedasticity and autocorrelation. Advanced economies (AEs) include 11 countries with data for most from 1973–2017.

c. Marginal Effect of FCI on Growth: EME
(OLS, conditional mean)

d. Marginal Effect of FCI on Volatility: EME
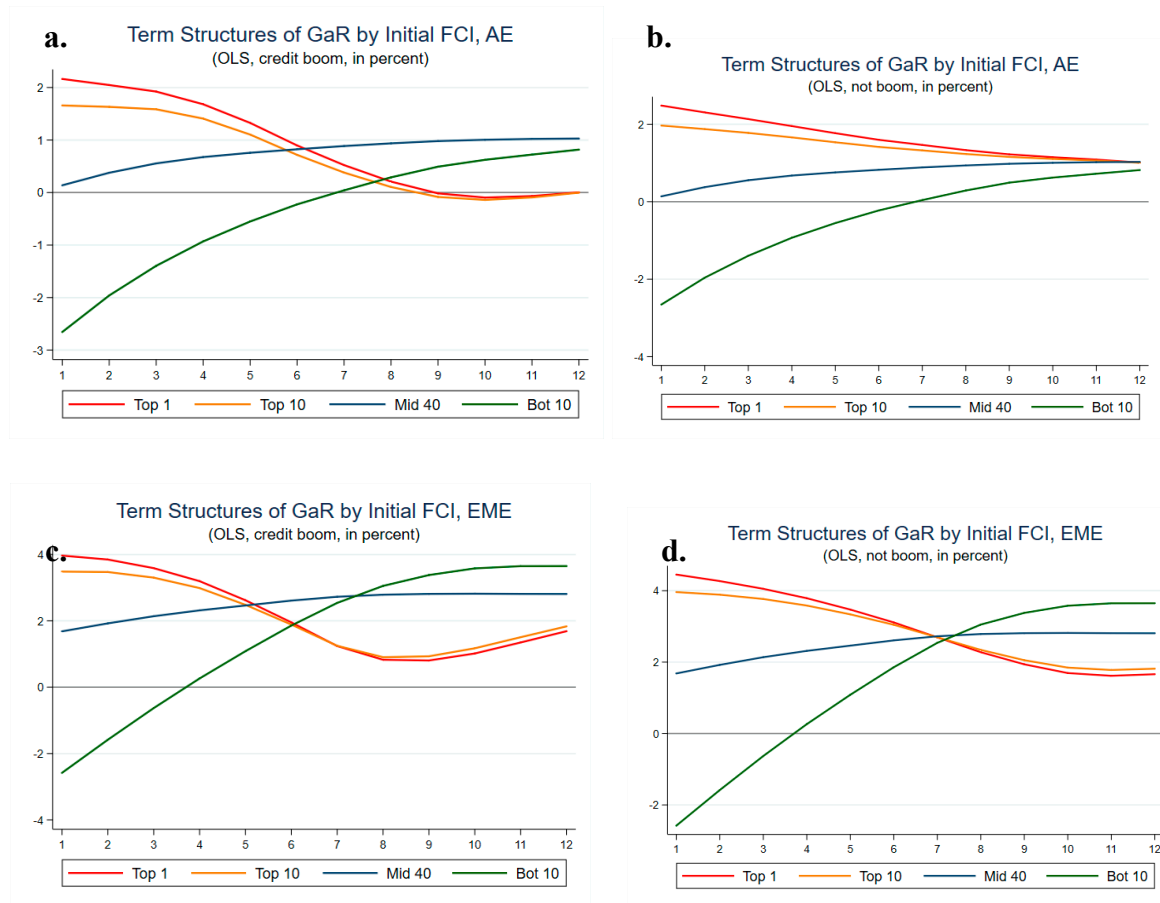(OLS, volatility)

Source: IMF staff estimates.

Note. Figures plot the estimated coefficients on the financial conditions index (FCI) and its interaction with high credit growth on GDP growth and GDP volatility for projection horizons from 1 to 12 quarters. Higher FCI represents looser financial conditions. Estimates are based on two-step OLS estimations, and standard errors are robust to heteroskedasticity and autocorrelation. Emerging market economies (EMEs) include 10 countries with data for most from 1996–2017.

Figure 10.Term Structures of GaR by Initial FCI Groups—From Two-Step OLS Estimations: AEs and EMEs

Source: IMF staff estimates.

Note. Figures plot the projected conditional growth-at-risk (expected growth at the 5th percentile), at an annual rate, based on estimations of the distribution of growth with the FCI and its interaction with high credit growth. The conditional grow-at-risk projections are sorted on initial financial conditions, for the Top 1 percent, top decile, bottom decile, and a middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on local projection estimation methods, and standard errors are robust to heteroskedasticity and autocorrelation. Advanced economies (AEs) include 11 countries with data for most from 1973 to 2017. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2017.

B.   Quantile Estimates for the AEs, Excluding the Global Financial Crisis

The sharp declines in GDP growth for many AE countries, along with the steep tightening of FCIs in 2008 when credit-to-GDP ratios had been rising, raises the possibility that this episode is driving the reported GaR results for the AEs. We test this possibility by removing the GFC years from our estimations.[17] The results indicate the estimates of GaR at *h*=4 tend

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[17] We remove the GFC observations by replacing the variables in 2008 to 2009 with the average of 2007 and 2010 values.

to be less negative from the baseline results, which is not surprising because we are removing the episode with the steepest decline in GDP growth in the sample period (Figure 11a). But, importantly, the projected conditional distribution continues to show greater downside variation than upside variation. In addition, the corresponding GaR term structures for initial Top 1 and Top 10 FCI continue to slope downward, though the slope is less steep (Figure 11b). We interpret these results as indicating that the estimated GaR reflect a general relationship between financial conditions and the distribution of expected growth over many decades, since the mid-1970s, but the results are strengthened when the GFC is included in the estimation.

Figure 11. Estimates after Excluding the Global Financial Crisis: AEs
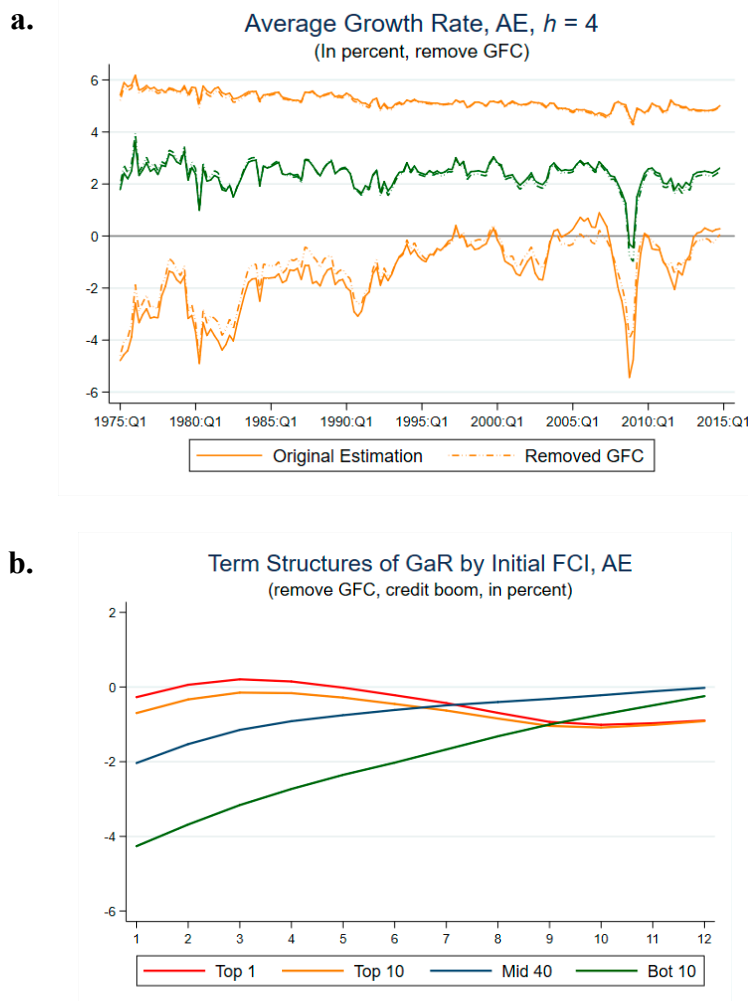
Source: IMF staff estimates.

C. Comparison of Quantile Regression Panel Estimates to U.S. Estimates

For comparison to Adrian et al. (2018), we show the results from our empirical model for the United States. Results are shown for *h*=4 from the quantile estimations based on just the U.S. data (Figure 12). The estimates for the United States clearly illustrate the intertemporal risk tradeoff. While the estimated GaR is higher for the U.S. than for AEs on average, the term structures for Top 1 and Top 10 show that the decline in GaR is similarly sizable, at about 3 percent. In addition, the estimations for the U.S. are very similar to Adrian et al. (2018), and demonstrate the results are robust to different FCIs and modest changes in the empirical model. The model in this paper differs because we add inflation and a credit boom dummy variable.

Figure 12. Projected Growth-at-Risk, Median, and 95th Percentile: the United States, at *h*=4

Source: IMF staff estimates.
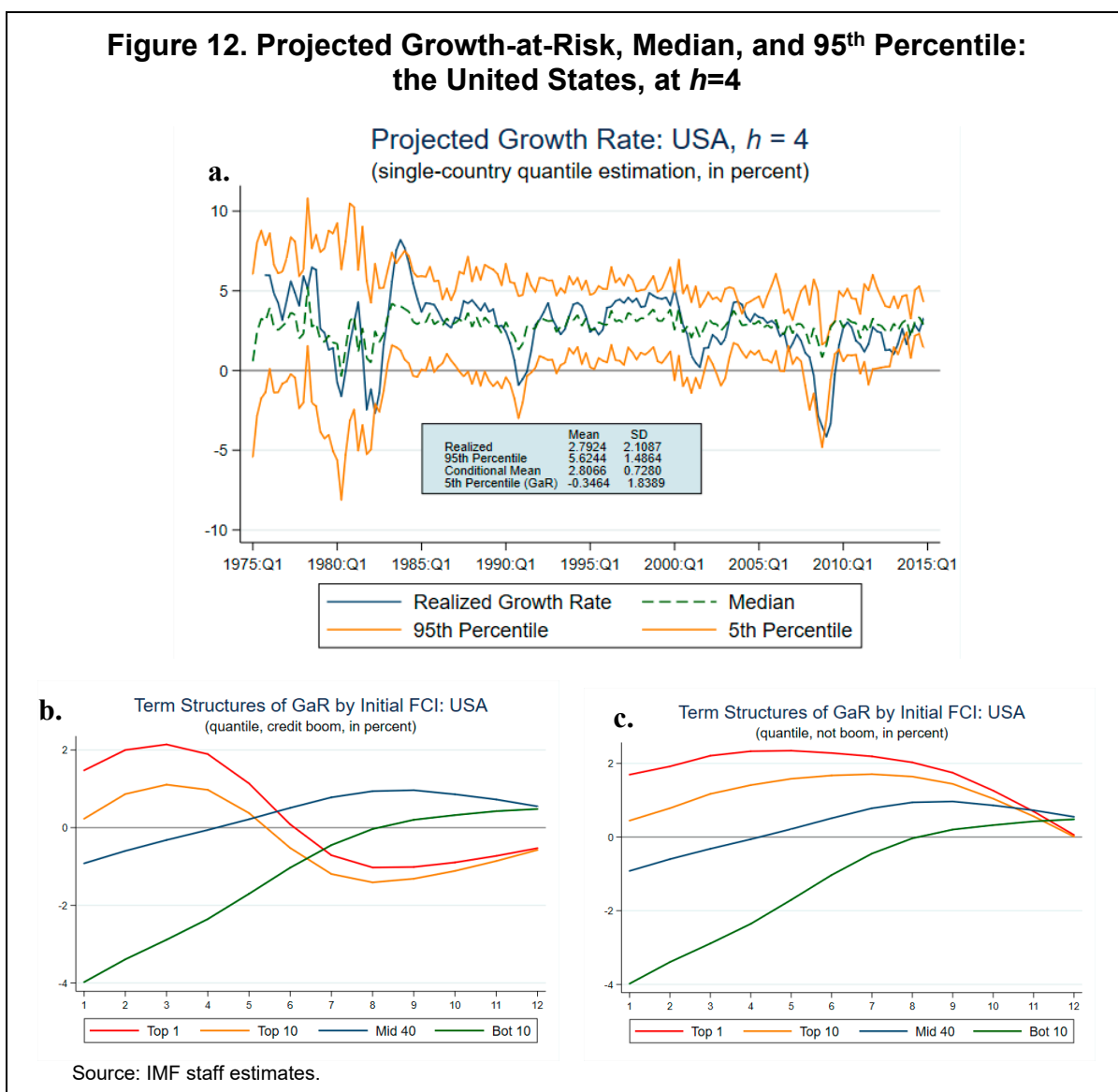
VI. CONCLUSION

Since the GFC and consequent damage to economic growth, more research has turned to exploring linkages between the financial sector and real economic activity. In this paper, we explore the empirical relationship between the financial conditions and the distribution of real GDP growth using data for 11 AEs from 1973 to 2017, and 10 EMEs from 1996 to 2017. The relationships we examine are rooted in macrofinancial linkages arising from financial frictions, such as asymmetric information and regulatory constraints, where low price of risk can lead to build-ups of financial vulnerabilities that then can generate negative spillovers and contagion when the price of risk reverses. We employ a model of output growth that depends on financial conditions, economic conditions, inflation, and credit growth, using panel quantile regressions. This method generates the term structure for the distribution of expected growth, and we focus on the lower 5th percentile of expected growth for horizons out to 12 quarters, which measures the term structure of GaR.

The main contributions of this paper are to show empirically that financial conditions affect the distribution of expected GDP growth and its effects change over the projection horizon, and are consistent with an intertemporal tradeoff at lower tails of the distribution. Of course, there are many studies that have linked financial conditions to growth—indeed, many argue that monetary policy affects the economy through financial conditions. But we show based on panel estimates for 11 AEs and 10 EMEs that financial conditions have strong forecasting power for the distribution, not just the mean, of expected growth, and that the signs of the coefficients on financial conditions reverse from the short- to medium-term horizons, especially for the lower tail of the distribution. Combined, the conditional expected growth distribution shifts with changes in financial conditions, with the lower tail—GaR—more responsive than the median or upper tail to financial conditions. Of particular significance, looser financial conditions imply higher GaR in the near term, but these effects reverse and imply a lower GaR (higher downside risk) in the medium term relative to initial moderate financial conditions. The differences in GaR between initial loose and moderate financial conditions are statistically different for both AEs and EMEs. Moreover, the additional boost to expected growth from initial loose financial conditions and high credit diminishes over the projection horizon, suggesting that expected growth has not increased to offset the costs of greater downside risks.

This empirical tradeoff is relevant to both macroeconomic forecasting and policymaking. The strong inverse correlation between conditional growth and conditional downside risk that we document is often ignored in dynamic macroeconomic models, which assume often for computation reasons that growth is not affected by volatility, and vice versa (certainty equivalence). This is an omission since tighter conditions in the near term may be beneficial for greater resilience, which could reduce large downside risks in the future.

The GaR measure that we develop offers promise as a way to translate financial stability risks to macroeconomic performance. While progress has been made to add macrofinancial

linkages, a dominant paradigm has not yet emerged about how to incorporate them into expanded models that would be used regularly by policymakers. This empirical model takes a step forward to integration. The GaR measure ultimately could help in developing macroprudential policies. t can provide an objective gauge for downside risks to expected growth and thus whether macroprudential policy interventions are needed, as well as a metric of whether interventions have been successful. For example, it could be used to help calibrate a countercyclical capital buffer, severity of stress tests, or borrower loan-to-value or loan-to-income ratios, to build the resilience of the financial system. While structural models are needed for policy evaluation, our measures offer important data calibrations to fit.

In addition, by expressing financial stability risks in terms of risks to output, they have the potential to be better incorporated into monetary policy decision making. When financial stability risks are expressed as the probability of a banking crisis, the discussion features discontinuous transitions of states, which sets up decision-making frameworks that consider the distribution of growth only intermittently. In our view, estimating the interplay of financial conditions and the conditional distribution in a continuous fashion has the advantage that it could become more relevant to policy making on a regular basis. Being able to express risks arising from the financial sector in the same terms as used in models for other macroeconomic policies will help when evaluating alternative policy options and foster more effective consultation and coordination.

APPENDIX I. START DATES FOR MODEL ESTIMATION AND FOR INDIVIDUAL COMPONENTS OF FCI: AEs AND EMEs

Country	Start date for estimation	Interbank Spread	Corporate Spread	Sovereign Spread	Term Spread	Equity Returns Volatility	Equity Returns	Change in real long-term rate	Change in FX
AUS	1975q1	1979q1	1983q2	1973q1	1979q1	1973q1	1973q1	1973q1	1970q1
CAN	1981q2	1973q1	1979q1	1973q1	1973q1	1973q1	1973q1	1973q1	1970q1
CHE	1980q2	1980q1	1982q1	1979q1	1980q1	1973q1	1973q1	1979q1	1970q1
DEU	1975q1	1979q1	1977q1	1977q1	1979q1	1973q1	1973q1	1977q1	1971q1
ESP	1992q1	1990q1	1990q1	1990q1	1990q1	1990q1	1990q1	1992q1	1971q1
FRA	1980q3	1979q1	1979q1	1977q1	1979q1	1973q1	1973q1	1973q1	1971q1
GBR	1975q1	1973q1	1979q1	1973q1	1973q1	1973q1	1973q1	1973q1	1970q1
ITA	1981q2	1979q1	1979q1	1977q1	1979q1	1973q1	1973q1	1973q1	1971q1
JPN	1975q3	1979q1	1973q1	1973q1	1979q1	1973q1	1973q1	1973q1	1970q1
SWE	1980q2	1979q1	1979q1	1979q1	1979q1	1973q1	1973q1	1979q1	1970q1
USA	1975q1	1973q1	1973q1	1973q1	1973q1	1973q1	1973q1	1973q1	1970q1
BRA	2006q4	2000q2	2001q4	1994q2	2007q1	1990q1	1990q1	2008q1	1994q3
CHL	1998q1	2005q4	2001q4	1999q2	1997q3	1990q1	1990q1	2006q3	1990q1
CHN	1998q1	2005q4	2002q2	1994q1	2005q4	1993q1	1993q1	2006q2	1990q1
IDN	1998q1	2003q1	2001q4	2004q2	2003q3	1990q1	1990q1	2004q3	1990q1
IND	1998q1	2000q2	2004q2	2003q1	2000q2	1990q3	1990q3	2000q1	1990q1
KOR	1998q1	2000q3	2001q4	1997q4	2000q4	1990q1	1990q1	2001q4	1990q1
MEX	1998q1	1990q1	2001q4	1993q4	2001q3	1990q1	1990q1	2002q3	1990q1
RUS	2006q1	2007q1	2002q2	1997q4	2007q1	1995q1	1995q1	2005q1	1992q3
TUR	1998q1	2007q3	2007q1	1996q2	2010q1	1990q1	1990q1	2011q1	1990q1
ZAF	1998q1	1990q1	2007q3	1994q4	1997q1	1990q1	1990q1	1998q1	1990q1

Country	VIX	MOVE	House price return	Change in equity market capitalization of financial sector to total market capitalization	Domestic commodity price inflation	Equity trading volume	Market capitalization for equities	Market capitalization for bonds	Expected default frequencies for banks
AUS	1986q1	1988q2	1973q1	2000q1	1970q1	1994q2	2001q1	1995q4	1999q4
CAN	1986q1	1988q2	1973q1	2000q1	1970q1	1990q4	2000q3	1995q4	1999q4
CHE	1986q1	1988q2	1973q1	2000q1	1970q1	1994q2	2002q4	1995q4	1999q4
DEU	1986q1	1988q2	1973q1	2000q1	1970q1	1993q4	1973q4	1995q4	1999q4
ESP	1986q1	1988q2	1990q2	2000q2	1970q1	1992q4	2001q2	1995q4	1999q4
FRA	1986q1	1988q2	1973q1	2000q1	1970q1	1993q4	1988q4	1995q4	1999q4
GBR	1986q1	1988q2	1973q1	2000q1	1970q1	1993q4	1986q4	1995q4	1999q4
ITA	1986q1	1988q2	1973q1	2016q1	1970q1	2004q2	2004q2	1995q4	1999q4
JPN	1986q1	1988q2	1973q1	2000q1	1970q1	1993q4	1989q4	1995q4	1999q4
SWE	1986q1	1988q2	1973q1	2000q1	1970q1	1993q4	2001q2	1995q4	1999q4
USA	1986q1	1988q2	1973q1	2000q1	1970q1	1990q4	2001q2	1995q4	1999q4
BRA	1990q1	1990q1	2008q2	2000q2	1990q1	1995q4	2001q2	1995q4	1999q4
CHL	1990q1	1990q1	2002q2	2000q2	1990q1	1996q2	2001q2	1995q4	1999q4
CHN	1990q1	1990q1	2003q2	1995q4	1992q1	2006q1	2005q4	1995q4	2001q2
IDN	1990q1	1990q1	1994q2	2001q1	1990q1	1996q4	1997q3	1995q4	1999q4
IND	1990q1	1990q1	2007q2	2000q2	1990q1	2000q4	2001q2	2000q4	1999q4
KOR	1990q1	1990q1	1990q2	2000q2	1990q1	2001q4	2006q2	1995q4	1999q4
MEX	1990q1	1990q1	2005q2	2000q2	1990q1	1995q4	2001q2	1995q4	1999q4
RUS	1990q1	1990q1	2000q2	2004q2	1996q1	2004q2	2004q2	1995q4	2000q2
TUR	1990q1	1990q1	2007q4	2000q2	1990q1	2004q4	2004q4	1995q4	1999q4
ZAF	1990q1	1990q1	2000q2	2000q2	1992q1	2003q3	2003q3	1995q4	1999q4

Sources: Bloomberg Finance L.P.; Thomsent Reuters Datastream; Bank for International Settlements; Haver Analytics; Moody's Analytics; Credit Edge; IMF, Global Data Sources, World Economic Outlook, and International Financial Statistics databases; United Nations, COMTRADE database; Dealogic; and IMF staff estimates.

APPENDIX II. PROBABILITY OF LOW GROWTH AT DIFFERENT HORIZONS: AES AND EMES

a. Probability of Low Growth (GaR<0%): AE, Top 1 fci

b. Probability of Low Growth (GaR<2%): EME, Top 1 fci
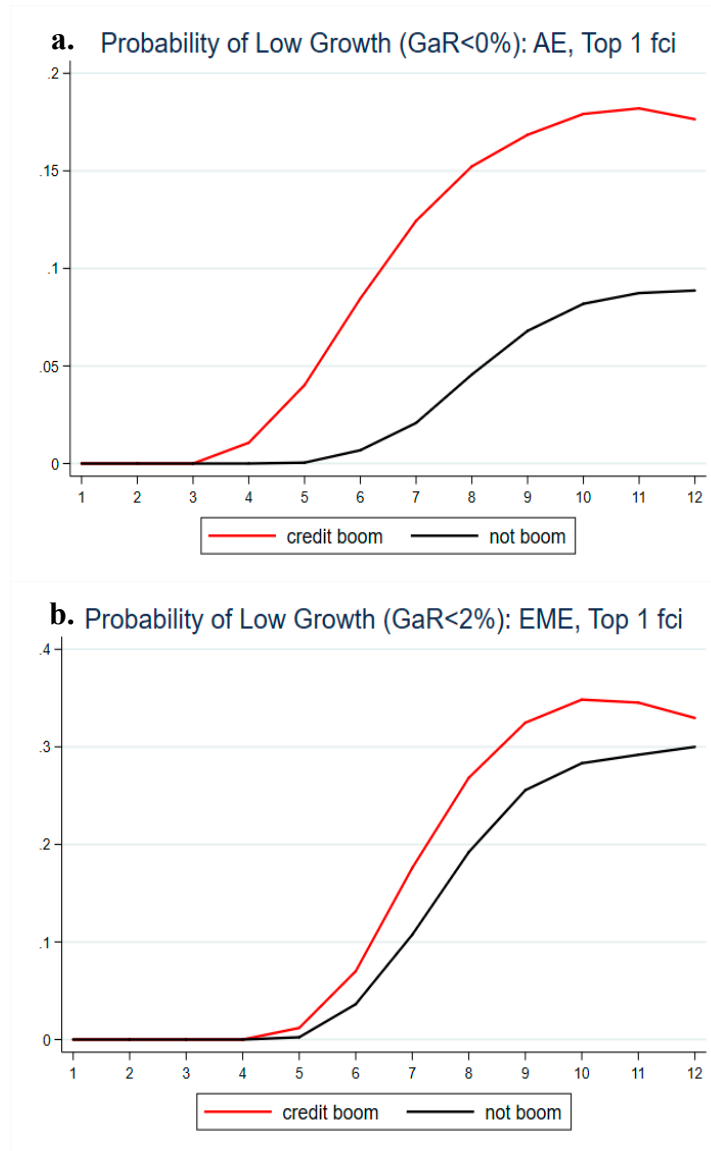
Source: IMF staff estimates.

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