The Term Structure of Growth-at-Risk

Tobias Adrian, Federico Grinberg, Nellie Liang, Sheheryar Malik*

May 16, 2018

Abstract

Using panels of 11 advanced and 10 emerging economies, we show that loose financial conditions mitigate downside risks to growth at short horizons, but then forecast higher risks at medium term horizons. That is, the term structure of growth-at-risk (GaR)—defined as conditional future growth at the lower 5th percentile—features an intertemporal tradeoff: Easy financial conditions are associated with GaR that is high in the short run, but low in the medium run. Moreover, the tradeoff is amplified by high credit growth. We provide evidence that the conditional expected growth distribution shifts with changes in financial conditions, with GaR more responsive than the median or upper tail. This change in distribution should be incorporated explicitly when solving dynamic stochastic general equilibrium models with macro-financial linkages. Also, the intertemporal risk-return tradeoff should be considered by policymakers when the costs of greater downside risks are high.

*Adrian: tadrian@imf.org, Grinberg: fgrinberg@imf.org, Liang: jliang@brookings.edu, Malik: smalik2@imf.org.

Jie Yu provided extraordinary research assistance. We thank Tommaso Mancini Griffoli, Frank Schorfheide, and participants at a BIS Research Network conference and an IMF workshop on GDP-at-risk. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the International Monetary Fund, its Board, or its Executive Directors.
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 5\textsuperscript{th} 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) 5\textsuperscript{th} 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).\textsuperscript{1} This model builds on estimations for the US in Adrian, Boyarchenko, and Giannone (2018). We also use local projections to estimate the dynamic response of GDP growth moments from one to twelve quarters, which allows us to explore the evolution of risk over the forecast horizon.

Figures 1a and 1b provide an illustration of the important role of financial conditions (FCI) for the modeling of the distribution of growth and the implied intertemporal risk-return tradeoff. In particular, the figures show the coefficient estimates on the financial conditions index (FCI) from panel quantile regressions for the lower 5\textsuperscript{th} 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

\textsuperscript{1} The 11 AEs include Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, Sweden, and the US. The 10 EMEs include Brazil, Chile, China, Indonesia, India, South Korea, Mexico, Russia, Turkey, and South Africa.
EMEs, respectively. Higher FCI is defined to represent looser financial conditions. The positive coefficients in near-term quarters for both the 5th percentile and median quantiles indicate that the marginal effects of looser financial conditions are to significantly boost growth. But the decline in coefficients over the projection horizon suggest the impetus from initial looser financial conditions will decline or subtract from average 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 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**

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 one to twelve 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 pricing of risk as measured by financial conditions. When asset prices rise, higher net worth eases borrowing constraints, and borrowers can accumulate credit which can become excessive because they do not consider negative externalities for aggregate demand (see, for example, Korinek and Simsek, 2016). Regulatory constraints for financial intermediaries also become less binding, leading to a reduction in risk premia, and excess risk-taking when vulnerabilities increase that leave the financial system less resilient to shocks (Adrian and Shin, 2014; He and Krishnamurthy, 2013). In addition, lower risk premia may be
associated with exuberant sentiment, consistent with empirical studies that corporate bond returns can be predicted based on sentiment two years earlier (Greenwood and Hanson, 2013). Moreover, predicted bond returns lead to a contraction in output as credit supply adjusts (Lopez-Salido, Stein, and Zakrajsek, 2017; Krishnamurthy and Muir, 2016).

Another feature of the empirical model is to 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 similar but more modest in magnitude.\(^2\)

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 empirical model shows 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 high credit growth is higher in the near-term and lower in the medium-term than GaR conditional on average FCI. For AEs, this difference is substantial. When FCIs are in the top 10 percent and credit growth is high, GaR falls about 3 percentage points, 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. Moreover, the derived probability density functions are highly skewed, and suggest the

\(^2\) In addition, the results are robust to using growth in the credit-to-GDP gap when the gap is positive.
probability of GaR falling to below 0 percent increases from a negligible level in the short-term to almost 20 percent in the medium-term. 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.

Another key result is that the 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. However, the additional growth diminishes moderately over the projection horizon, while GaR falls sharply, indicating the increased downside risks are not counter-balanced by expectations of higher growth.

Finally, we obtain qualitatively similar results to the quantile estimates when we use a two-step 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 between the quantile and two-step estimation suggest the model is robust to alternative estimation methods, and is promising for forecasting since the two-step procedure may be easier to incorporate into regular macroeconomic forecasting exercises.

The empirical results in this paper have important implications for macroeconomic models and 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. Hence, empirical models of macrofinancial linkages need to incorporate the endogeneity of first and higher-order moments. Moreover, the covariation of conditional first and higher moments are present at horizons out to twelve quarters.

The term structure of GaR also points to a need for policymakers to consider an intertemporal risk-return tradeoff. 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 macro-financial 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. 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 greater coordination.

Our paper is related to empirical studies of the effects of financial conditions on output. As mentioned, we build on Adrian, Boyarchenko, and Giannone (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 twelve-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 2 presents the stylized model of GDP growth and financial conditions, describes the quantile regression estimation method, and Section 3 presents the data. Section 4 defines GaR and presents estimates of the conditional GDP distribution and the importance of including FCIs. Section 5 provides results using the two-step OLS regression method and shows the results for GaR are similar to results from quantile estimations, suggesting the results are robust to estimation methods. Section 6 concludes.

2. Modeling Growth-at-Risk

We build on the Adrian, Boyarchenko, and Giannone (2018) who estimate the expected conditional GDP growth distribution for the US. 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 one to twelve 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-term and
medium-term horizons, defined roughly as one-to-four quarters out and five-to-twelve quarters out, respectively. We expand the sample to 21 countries and allow for nonlinearities from financial vulnerabilities, approximated by high credit growth.

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, lagged GDP growth, inflation, a dummy variable for 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 $\delta_{\alpha}$ is chosen to minimize the quantile weighted absolute value of errors

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

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

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

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

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

where $GaR_{i,h}(\alpha | \Omega_t)$ is growth at risk for country $i$ in $h$ quarters in the future at a $\alpha$ probability. Concretely, GaR is implicitly defined by the expected average growth rate between periods $t$ and $t+h$ given $\Omega_t$ (the information set available at $t$) for a given probability $\alpha$. For a low value of $\alpha$, GaR will capture the expected growth at the lower end of the GDP growth distribution. We define GaR to be the lower 5th percentile of the GDP growth distribution. That is, there is 5 percent probability that growth would be lower than GaR.

We use the average of cumulative growth rates to make it easier to interpret the units, rather than
cumulative growth rates sometimes used in other applications of the local projection method.\textsuperscript{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,\textsuperscript{4} while at the same time having a model that does not impose dynamic restrictions embedded in 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.

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).\textsuperscript{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 $(y,x)$-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. Resampling rows assumes some degree of independence of observations across time (iid). However, 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. In the analysis below, we generate bootstrap standard errors considering block widths of 4, 6 and 10 quarters, but report only block widths of

\textsuperscript{3} For example, Jorda (2005), Jorda, Schularick and Taylor (2013).
\textsuperscript{4} See Jorda (2005) and Stock and Watson (2018).
\textsuperscript{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, and Canay, 2011). In general, estimation and associated asymptotic properties are based on restricting fixed-effects to be invariant across different quantiles.
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 Capitanio (2003) in order to smooth the quantile function:

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

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 \(\mu\), scale \(\sigma\), fatness \(\nu\), and shape \(\theta\). 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 \(\lambda_{i,t}\) 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. We use the growth in the private nonfinancial credit-to-GDP ratio, measured over the previous eight quarters. We define a dummy variable for the potential for a credit boom by when both FCI and growth are in the top three deciles of their distributions respectively.\(^6\)

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

\(^6\) As an alternative, we use growth in the private nonfinancial credit-to-GDP gap when it is high and the gap is positive. The credit-to-GDP gap is a variable proposed by the Basel Committee as an indicator of an important financial vulnerability. When the credit gap is high, 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.
VAR model of the US, where the interaction of financial conditions and the credit-to-GDP gap lead to higher volatility of GDP in the US (Aikman, Liang, Lehnert, Modugno, 2017). Brunnermeier et al (2017) find that credit affects the transmission of monetary policy and financial conditions in the US.

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

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

That is, when the conditions for a credit boom are relatively high, $\lambda_{i,t}$ takes a value of 1. In all other states $\lambda_{i,t}$ takes a value of zero. In the alternative specification based on growth in the credit-to-GDP gap, we use the BIS measures which apply the HP filter to nonfinancial private credit as a percent of GDP and using a smoothing coefficient of 400,000.

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, lower GaR, in the medium-term.

Our empirical model aims to capture the dynamics following a loosening of financial conditions, allowing for nonlinearities. We test whether the immediate benign growth conditions are sustainable or if volatility and downside risk increase in the medium term. To fix ideas, changes in the distribution of GDP growth are generated by changes in the pricing of risk, which are financial conditions. Changes in the pricing of risk can arise from frictions, such as VaR or capital constraints of financial intermediaries, which tie together volatility and the price of risk via the credit supply of intermediaries (Adrian and Shin, 2014; He and Krishnamurthy, 2012, 2013). When asset prices rise and constraints become less binding, financial conditions loosen and GDP growth increases and its distribution tightens. However, the lower price of risk and lower volatility can contribute to an increase in financial imbalances, such as higher borrowing,
which would lead to a sharper rise in volatility when an adverse shock hits, referred to as the volatility paradox (Brunnermeier and Sannikov, 2014).

In addition, time-varying risk premia suggest that periods of compressed risk premia can be expected to be followed by a reversal of valuations. 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.

The model can be directly interpreted within the setting of Adrian and Duarte (2016) who model macro-financial 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 pricing of risk, which we measure using a financial conditions index. Time variation in the price of risk is generated by value at risk constraints of financial intermediaries who intermediate credit. Hence the conditional volatility of output growth is driven by the pricing of risk. Adrian and Duarte (2016) show that optimal monetary policy depends on downside risks to GDP, and hence the conditional mean of GDP growth also depends on financial conditions.

3. Data

Quarterly data for real GDP growth and consumer price indexes (CPI) to measure inflation (year-to-year percent change) for the 21 countries are available from the International Financial Statistics (IFS). Combined, the 21 countries represent 74 percent of world GDP in 2017. Nonfinancial credit-to-GDP ratios are from the BIS, and credit is to households and businesses.

The FCIs for the 21 countries are constructed using data on up to 17 variables, from the IMF October 2017 Global Financial Stability Report (GFSR), Chapter 3. FCIs are a parsimonious way to summarize the information in asset prices. The FCIs used in this study reflect domestic and global financial price factors that influence a country’s financial conditions, such as corporate credit spreads, equity prices,
volatility, and foreign exchange. An important advantage of these FCIs is that they have been constructed on a consistent basis for a relatively long sample time period and across a large number of countries.

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). This approach has three advantages: (i) it can purge 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.

The model takes the following form:

\[
Z_t = \theta^Y_t Y_t + \theta^f_t f_t + v_t
\]

\[
\begin{align*}
Y_t & = c_t + B_{t-1} Y_{t-1} + \ldots + B_{t-p} Y_{t-p} + \epsilon_t \\
Y_t & = B_{t-1} Y_{t-1} + \ldots + B_{t-p} Y_{t-p} + \epsilon_t
\end{align*}
\]

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), \(\theta^Y_t\) are regression coefficients, \(\theta^f_t\) are the factor loadings, and \(f_t\) is the latent factor, interpreted as the FCI.

The FCIs used in the October 2017 GFSR were constructed in a way to distinguish between periods of low and normal GDP growth. They also included two credit variables, which we excluded, preferring to allow the credit variables to affect the distribution of growth separately from the price of risk. For

7 The variables include corporate spread, sovereign spread, term spread, interbank 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, VIX.

8 Specifically, the construction of the FCIs for the October 2017 GFSR differs from the standard Koop and Korobilis (2014) approach because it also discriminates one-year-ahead growth below the 20th percentile of historical outcomes from expected growth. That is, the FCI is designed to distinguish between periods of low GDP growth and normal GDP growth.
robustness, we test the sensitivity of our results to the FCIs in the GFSR, but rely more heavily on results that are constructed in a more traditional way without credit.

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 data for most of the 11 AEs are for 1973 to 2017, and data for most of the 10 EMEs are from 1996 to 2017. The exceptions for AEs are data for Japan start in 1975:q2, France 1980:q3, and Spain in 1990:q1. The exceptions for EMEs are data for Turkey start in 1996:q3, Russia 2006:q1, and Brazil 2006:q4. The long sample period for the AEs, and to a lesser extent the EMEs, allows us to capture multiple business and credit cycles, rather than only the global financial crisis.

TABLE 1 HERE]

There are some important differences between the AEs and EMEs, supporting our choice to estimate separate panels. Not surprisingly, growth is higher in the EMEs than the AEs, about twice as fast on average. 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 quarterly growth rates and higher credit-to-GDP gaps. Periods when the credit boom $\lambda$ 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 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. Charts of FCI and credit-to-GDP growth for all of the 21 countries in our sample are in Appendix A. These 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.

4. Empirical Results

In this section, we show that the addition of credit boom conditions – loose FCI and high credit growth – suggest the role of FCI on the distribution of growth is consistent with credit as an amplification
mechanism. We then illustrate 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 lambda. 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 were loose than when they were average. This comparison provides an estimate of the inter-temporal risk tradeoff relative to normal 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 $\lambda$ for the 5th percentile quantile regressions over the projection horizons, for AEs and EMEs, respectively. The coefficients on $\lambda$ 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 $\lambda$ 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 HERE]

The significant coefficients for $\lambda$ 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.

[Figure 3 HERE]

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 0.31, 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 -1.2 percent with a standard deviation of 1.75 percent, while the standard deviation of the 95th percentile is 0.22 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 US only. Below
we present the time series results for the US only, as a comparison to Adrian et al (2018) (see section 5b, figure 16).

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 high credit growth 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 shift in the distribution suggests downside risks have increased considerably from $h=4$ to $h=10$ for these initial conditions.

[Figures 4 and 5 HERE]

We can also express the downside risks as the probability of GaR falling below zero at each projection horizon for $h =1$ to 12 implied by the distributions (figure 4b). As shown, this probability is negligible in the near-term but rises significantly to almost 20 percent in the medium-term for these initial conditions. In contrast, for high FCI but without high credit growth, the shift in the distribution between $h=4$ and $h= 10$ is less pronounced (figure 4c), and the probability of negative growth rises more modestly from zero to about 9 percent (figure 4d).

For EMEs, the distributions are fatter than for the AEs, but changes between $h=4$ and $h= 10$ exhibit similar patterns. The conditional growth distribution at $h=4$ has a smaller left tail and a higher mean than the distribution at $h= 10$ (figure 5a). The risk of the probability of GaR dropping below 2 percent is about 0 percent in the near-term but is substantially higher at 35 percent in the medium-term with initial credit boom conditions (figure 5b), and a bit less at 30 percent when initial FCI was high but credit growth was not (figures 5c and 5d). Note that there is a shift in the conditional mean for EMEs that is not evident for AEs, which suggests differences in the dynamics of growth between these two sets of countries.

d. Term structures of GaR by initial FCI group

Next we show the term structure of GaR based on a number of different initial FCI groups. We show GaR term structure estimates based on initial average FCI values for four groups: in the top 1 percent
When initial FCIs are in the top decile or higher, the estimated GaRs show a downward slope over most of the projection horizon, indicating lower downside risk in the short-term and higher downside risks in the medium-term (figure 6a and 6b). These term structures indicate an inter-temporal tradeoff for risk, with GaR falling below zero at horizons of four and six quarters when credit growth is high, and at eight quarters when credit growth is not high. For AEs, very loose FCIs (top 1) and high credit are associated with GaR of more than 1 percent in the near-term, which falls significantly over the projection horizon to less than -2.0 percent at around \( h = 8 \), a swing of more than 3 percent; the swing for FCI in the top decile is about 2.5 percent. We use the mid 40 percent group based on initial FCI values to represent neutral 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 hover near -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.

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 between the average FCI in the top 1 with high credit and mid 40 are positive and statistically significant in the near-term and turn negative and statistically significant in the medium-term (figure 7a), indicating that the lower downside risks in the near-term from the loose FCI reverse and become larger in quarters further out. The difference when credit growth is low is also positive and significant in the short-term, and falls over the projection horizon, but the magnitude of the decline is smaller (figure 7b). When credit growth is high, the difference in GaR is about 2 percentage points lower at around \( h = 8 \) to 10 than when credit growth is low, suggesting credit growth plays an important role in amplifying changes in financial conditions, consistent with theories of macro-financial linkages.

For EMEs, the term structures are similar to those for AEs for the same initial FCI groups, though GaR is higher across the projection horizons and stays above zero (figures 8a and 8b). The differences in the term structures for average FCI values in the top 1 and mid 40, for both high credit and low credit, also are statistically different (figures 9a and 9b).
Returning to the term structures in figures 6 and figures 8, 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, suggesting the economy is in a deep recession or a financial crisis. However, these effects dissipate over time and converge to conditions for initial moderate financial conditions in the medium run. 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.

c. Term structures of expected median and GaR by initial FCI groups

So far, we have focused on GaR, the lower tail of the expected growth distribution. But another important issue is the term structure for expected growth when initial FCI is loose and credit growth is high. In this section, we evaluate the projected additional growth and reduction in downside risks from loose financial conditions relative to neutral over the term structure. We find that the projected additional growth falls moderately over the projection horizon, but the reduction in downside risks falls substantially. That is, conditioning on loose FCI and high credit relative to average FCI, the intertemporal risk tradeoff – less risk now at the cost of more risk later – is not mitigated by higher 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 10). While the median and GaR term structure projections vary across the 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 (average) in all cases, and the gap shrinks over time, mostly as the median projected 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. For the case of high credit, the reversal is substantial. Note
also that projected median growth for neutral FCI is flat over the projection horizon, at slightly under 2 percent for AEs and 3 percent for AEs, 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 10 HERE

Figure 11 plots the information in figure 10 as differences in the term structures between the top decile and the neutral case for the projected medians and GaR. What is more evident from the differences is that the decline in GaR is much steeper than the decline in the median growth in all four cases. For AEs with high credit, the estimates indicate that the marginal boost to growth from loose financial conditions relative to average diminishes somewhat, but there is a sharp decline in GaR (sharp increase in downside risks). This configuration illustrates the costs of a credit boom. When credit is low, the marginal boost to growth from loose initial financial conditions is quite modest, but the decline in GaR – the amplification effect -- is less sharp. This configuration illustrates a situation of slower growth but also lower downside risks. For EMEs, while GaR declines over the projection horizon, the decline is less sharp than in the AEs, indicating the magnitude of a risk-return tradeoff is quite different. Moreover, the estimates are not substantially different between high and low credit for GaR, suggesting high credit growth may not play the same role in EMEs as in AEs.

Figure 11 HERE

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 are statistically different. While we do not model the determination of FCIs, the increased downside risks in the medium-term associated with looser financial conditions (lower price of risk) suggests that policymakers could take actions to reduce future downside risks by tightening financial conditions when they are very loose and credit growth is high.

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. 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 unsustainable levels.

5. Robustness

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:

$$
\Delta y_{t+h} = y_0^{(h)} + y_1^{(h)} f_{t,t} + y_2^{(h)} y_{t,t} + y_3^{(h)} \pi_t + y_4^{(h)} \lambda_{t,t} + \epsilon_{t,t} \quad h = 1, \ldots, 12
$$

9 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).
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 a i.i.d. Gaussian error term. This model can be thought of as a panel extension of an ARCH model where 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 \( \ln \varepsilon_{i,t+h}^2 \) onto the right-hand side variables of equation (9). \(^{10}\) 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. \(^{11}\) Standard errors are computed using Newey West standard errors that correct for the autocorrelation in the 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:

\[
(10) \quad GaR_{i,t+h}(\alpha) = E \left( \Delta y_{i,t+h} \mid \Omega_t \right) + N^{-1}(\alpha)Vol \left( \Delta y_{i,t+h} \mid \Omega_t \right)
\]

where \( GaR_{i,t+h}(\alpha) \) is growth at risk for country \( i \) in \( t+h \) quarters in the future at a \( \alpha \) probability, \( E \left( \Delta y_{i,t+h} \mid \Omega_t \right) \) is the expected mean growth for period \( t+h \) given the information set \( \Omega_t \) available at \( t \).

\(^{10}\) Note that the estimated residuals \( \varepsilon_{i,t} \) are not a “generated regressor” and thus they can be used directly in the second stage equation (see Pagan, 1984).

\(^{11}\) Given the assumption of a conditional Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth.

\(^{12}\) Adrian and Duarte (2017) show that for a low value of \( \alpha \) this is a good approximation as higher order terms go rapidly to zero.
obtained by fitting equation (8). $Vol(\Delta y_{i,t+h} | \Omega_t)$ 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 $\alpha$. As above, $\alpha$ is fixed at 5%, 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 12a). At the same time, the coefficients for volatility are negative in the near-term and increase over the projection horizon (figure 12b). The same pattern holds for EME growth and volatility coefficients (figures 13a and 13b). These results suggest an intertemporal tradeoff of higher growth in the near term and lower growth with higher downside risks in the medium-term.

[Figures 12 and 13 HERE]

We derive the GaR term structures and condition on initial FCIs. Figures 14 and 15 are the counterparts to figures 6 and 8, 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 inter-temporal tradeoff found with the quantile regressions.

[Figures 14 and 15 HERE]

b. Comparison of quantile regression panel estimates to US estimates

For comparison to Adrian et al (2018), we show the results from our empirical model for the US. Results are shown for $h=4$ from the (a) panel quantile estimations with US country fixed effects and from (b) quantile estimations based on just the US data (figure 16). The two projected distributions are very similar, and both clearly demonstrate greater downside risk variability than upside variability. Also, the estimations based on the panel show that the projections for the US are not too different from the average AE in the panel (shown in figure 3a). Moreover, the estimations from the model in this paper based just
on US data are very similar to Adrian, et al 2018, and demonstrate the results are robust to using different FCIs and changes in the empirical model. The model in this paper differs because we add inflation and a credit boom dummy variable.

[Figure 16 HERE]

6. Conclusion

Since the global financial crisis 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 which 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 twelve quarters, which measures the term structure of growth-at-risk.

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 tradeoff has implications for 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 a significant oversight since it ignores that tighter conditions in the near-term may be beneficial for greater resilience to 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 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. It 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.
References


<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev</th>
<th>Median</th>
<th>10th Percentile</th>
<th>90th Percentile</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>a. Advanced Economies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>0.0221</td>
<td>0.0346</td>
<td>0.0245</td>
<td>-0.0161</td>
<td>0.0594</td>
<td>1576</td>
</tr>
<tr>
<td>Inflation Rate</td>
<td>3.4636</td>
<td>3.3448</td>
<td>2.5977</td>
<td>0.3417</td>
<td>7.9407</td>
<td>1576</td>
</tr>
<tr>
<td>Transformed FCI</td>
<td>0.0181</td>
<td>1.0431</td>
<td>-0.0029</td>
<td>-1.1757</td>
<td>1.3803</td>
<td>1576</td>
</tr>
<tr>
<td>Credit Boom Dummy</td>
<td>0.0774</td>
<td>0.2573</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1576</td>
</tr>
<tr>
<td>credit to GDP Gap</td>
<td>0.0198</td>
<td>0.1050</td>
<td>0.0190</td>
<td>-0.1000</td>
<td>0.1370</td>
<td>1576</td>
</tr>
<tr>
<td>Credit to GDP Growth</td>
<td>0.0055</td>
<td>0.0107</td>
<td>0.0047</td>
<td>-0.0066</td>
<td>0.0185</td>
<td>1576</td>
</tr>
<tr>
<td><strong>b. Emerging Market Economies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>0.0447</td>
<td>0.0613</td>
<td>0.0476</td>
<td>-0.0100</td>
<td>0.1070</td>
<td>613</td>
</tr>
<tr>
<td>Inflation Rate</td>
<td>7.1502</td>
<td>9.2600</td>
<td>4.9794</td>
<td>1.5814</td>
<td>11.1104</td>
<td>613</td>
</tr>
<tr>
<td>Transformed FCI</td>
<td>-0.0192</td>
<td>1.0842</td>
<td>-0.1160</td>
<td>-1.1728</td>
<td>1.3870</td>
<td>613</td>
</tr>
<tr>
<td>Credit Boom Dummy</td>
<td>0.0799</td>
<td>0.2714</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>613</td>
</tr>
<tr>
<td>credit to GDP Gap</td>
<td>0.0078</td>
<td>0.1061</td>
<td>0.0230</td>
<td>-0.1280</td>
<td>0.1190</td>
<td>613</td>
</tr>
<tr>
<td>Credit to GDP Growth</td>
<td>0.0043</td>
<td>0.0144</td>
<td>0.0046</td>
<td>-0.0101</td>
<td>0.0190</td>
<td>613</td>
</tr>
</tbody>
</table>

Note. Table includes descriptive statistics for 11 advanced economies and 10 emerging market economies. The 11 AEs include Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, Sweden, and the US. The 10 EMEs include Brazil, Chile, China, Indonesia, India, South Korea, Mexico, Russia, Turkey, and South Africa. Most of the advanced economies have data for the full sample period 1973 to 2017, but data for Japan start in 1975:q2, France 1980:q3, and Spain in 1990:q1. Most of the emerging market economies have data for the full sample period 1996 to 2017, but data for Turkey start in 1996:q3, Russia 2006:q1, and Brazil 2006:q4.
Figure 2. Coefficient estimates on credit boom for 5th percentile, AEs and EMEs

Note: Figures 2a and 2b plot the estimated coefficients on the credit boom dummy variable from panel quantile regressions for the 5th percentile, from one 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.
Figure 3. Average Growth-at-Risk, Median, and 95th Percentile at h=4, AEs and EMEs

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 include 11 countries with data for most from 1973 to 2017. Emerging market economies include 10 countries with data for most from 1996 to 2017.
Figure 4. Probability density function of conditional GDP growth at different horizons, AEs

Note. Probability of growth falling below zero is the area under the densities less than or equal to zero percent. Advanced economies include 11 countries most with data from 1973 to 2017.
Figure 5. Probability density function of conditional GDP growth at different horizons, EMEs

Note. Probability of growth falling below two is the area under the densities less than or equal to two percent. Emerging market economies include 10 countries most with data from 1996 to 2017.
Figure 6. Term structures of GaR by initial FCI, AEs

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 include 11 countries with data for most from 1973 to 2017.

Figure 7. Testing the differences between GaR term structures

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 include 11 countries with data for most from 1973 to 2017.
Figure 8. Term structures of GaR by initial FCI, EMEs

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.

Figure 9. Testing the differences between GaR term structures

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 10. Term structures by initial FCI: Conditional Median and GaR, AEs and EMEs

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 include 11 countries with data for most from 1973 to 2017. EMEs include 10 countries with data for most from 1996 to 2017.
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 include 11 countries with data for most from 1973 to 2017. EMEs include 10 countries with data for most from 1996 to 2017.
Figure 12. Marginal effects of FCI on growth and volatility from two-step OLS estimations, AEs

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 one to twelve 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 include 11 countries with data for most from 1973-2017.

Figure 13. Marginal effects of FCI on growth and volatility from two-step OLS estimations, EMEs

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 one to twelve 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 include 10 countries with data for most from 1996-2017.
Figure 14. Term structures of GaR, by initial FCI, two-step OLS estimation, advanced economies.

Figure 15. Term structures of GaR, by initial FCI, two-step OLS estimation, Emerging market economies.

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. 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 include 11 countries with data for most from 1973 to 2017. Emerging market economies include 10 countries with data for most from 1996 to 2017.
Figure 16. Average Growth-at-Risk, Median, and 95th Percentile, at h=4
Appendix A: FCI and Credit-to-GDP growth

a. Advanced economies

Transformed FCI vs Credit-to-GDP Growth Rate

AUS

Transformed FCI vs Credit-to-GDP Growth Rate

CAN

Transformed FCI vs Credit-to-GDP Growth Rate

CHE

Transformed FCI vs Credit-to-GDP Growth Rate

DEU

Transformed FCI vs Credit-to-GDP Growth Rate

ESP

Transformed FCI vs Credit-to-GDP Growth Rate

FRA
b. Emerging market economies