The Term Structure of Growth-at-Risk

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Abstract

Using panels of 11 advanced and 10 emerging economies, we show that loose financial conditions forecast high economic growth and low economic volatility at short horizons, but then forecast low growth and high volatility at medium term horizons. Accordingly, the term structure of growth-at-risk (GaR)--defined as conditional future growth at the lower 5th percentile--features a volatility paradox: Easy financial conditions are associated with GaR that is high in the short run, but low in the medium run. Moreover, the volatility paradox is amplified in a credit boom. Our findings point to an intertemporal risk-return tradeoff that can be economically significant. We argue that this inverse relationship between conditional mean and volatility over time should be incorporated explicitly in dynamic stochastic general equilibrium models with macro-financial linkages. The intertemporal risk-return tradeoff also is significant for policymakers as policies that boost growth in the short term may increase future downside risks.

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I. Introduction

Financial conditions affect expected growth and its variance. But macroeconomic models and forecasting practices predominantly focus on expected growth, and usually do not explicitly model the full forecast distribution. Dynamic stochastic general equilibrium models tend to focus on impulse response functions that depict conditional growth, and which assume that the mean and variance are independent. This focus on conditional growth can be too narrow as the full distribution of expected growth is important when future volatility depends on current growth and financial conditions, consistent with endogenous risk-taking.

In this paper, we estimate the distribution of expected GDP growth from economic and financial conditions for 21 countries, a panel of 11 advanced economies (AEs) and of 10 emerging market economies (EMEs).[1] We estimate a heteroskedastic variance model using a two-step local projection estimation method for the AEs from 1973 to 2016, and the EMEs from 1996 to 2016. We build on Adrian, Boyarchenko, and Giannone (2016), who present estimates of growth distributions in the US as a function of financial and economic conditions. They show that the expected distribution at one quarter and four quarters ahead changes when financial conditions tighten, with both the center and the lower quantiles of the distribution of economic growth falling significantly. We expand their framework to 21 countries and use a local projections estimation method to estimate the dynamic response of GDP growth moments from one to twelve quarters, rather than evaluating estimates at two points in the future. 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). In addition, the two-step estimator for the term structure of conditional means and conditional variances offers a simpler way to empirically derive the forecast distribution at various time horizons, which makes it more practical for ongoing policymaking. We also show, based on preliminary estimations, that our results hold when we use the quantile regression approach of Adrian et al (2016).

[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.

Figure 1. Estimated coefficients on FCI for growth and volatility - Advanced Economies

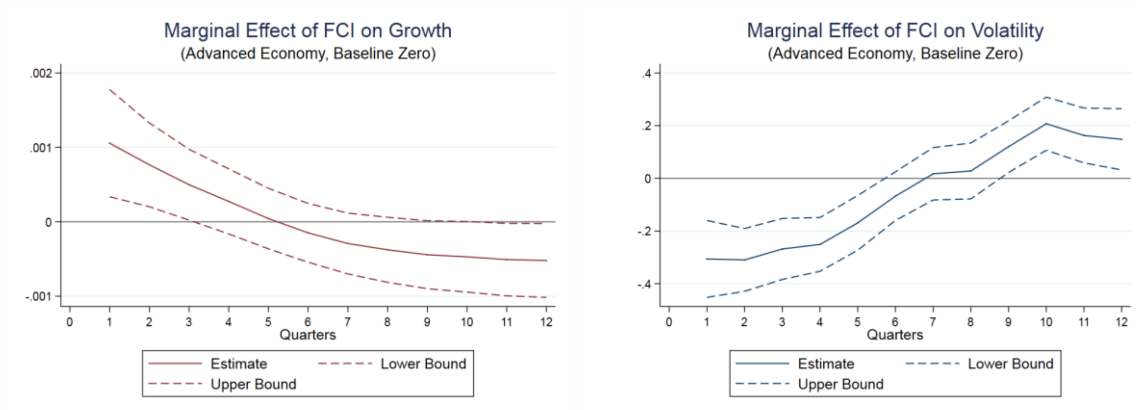
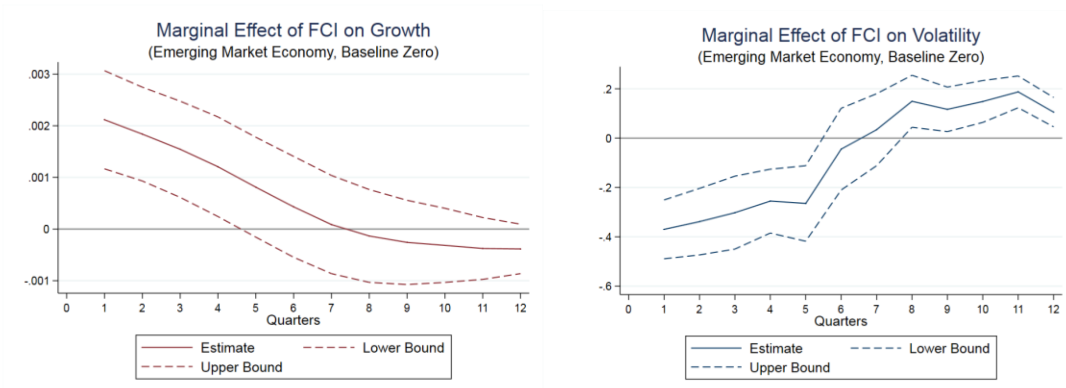


Figure 2. Estimated coefficients on FCI for growth and volatility - Emerging Market Economies



Note: The figures plot the estimated coefficients on the financial conditions index (FCI) on GDP growth and GDP volatility 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 robust to heteroskedasticity and autocorrelation. Advanced economies (AEs) include 11 countries with data for most from 1973-2016. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2016.

Figures 1 and 2 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 of FCI on average GDP growth (quarterly rate for the cumulative period ending in quarters 1 through 12) and on volatility of growth for AEs and EMEs, respectively. Higher FCI is defined to represent looser financial conditions. The positive coefficients in near-term quarters indicate that looser financial conditions boost average cumulative growth, but the decline in coefficients over the projection horizon suggest initial looser conditions will reduce growth in quarters further out, at about nine quarters and more out. At the same time, the negative coefficients of FCI on volatility suggest that looser financial conditions reduce average growth volatility in the short term, but the increase in coefficients over the projection horizon suggest that the initial looser conditions lead to higher volatility further out. That is, the signs of the estimated coefficients for growth and volatility switch as the horizon lengthens, which provides strong empirical support for an intertemporal risk-return tradeoff generated by financial conditions.

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 excess credit but 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 further reduction in risk premia and higher leverage (Adrian and Shin, 2014; He and Krishnamurthy, 2013). Further loosening of conditions may lead to excess risk-taking and an increase in vulnerabilities that leaves the financial system less resilient to shocks. In addition, lower risk premia may be associated with exuberant sentiment, consistent with empirical studies that corporate bond returns that can be predicted based on sentiment two years earlier. Moreover, predicted bond returns lead to a contraction in output as credit supply adjusts (Lopez-Salido, Stein, and Zakrajsek, 2017; Krishnamurthy and Muir, 2016). We explore our pricing of risk interpretation more fully below.

We start by describing the empirical model of expected output growth with heteroskedastic volatility which depends on financial and economic conditions. Given the assumption of a conditionally Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth. By going beyond estimating only the mean for different horizons, we can evaluate whether the higher growth and lower volatility achieved with looser financial conditions in the near-term are long-lasting and sustainable.

Using the estimated moments of the distribution of expected GDP growth, we construct a growth at risk measure (GaR) for each time horizon. Concretely, GaR is defined by 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. That is, there is 5 percent probability that growth would be lower than GaR. Thus, higher growth and lower volatility would lead to a higher GaR, and lower growth and higher volatility would lead to a lower GaR.

Another feature of the empirical model is to allow for nonlinear effects of FCIs on the growth distribution by interacting the FCI with financial vulnerabilities that could amplify a negative shock. This interaction allows us to test for whether excess credit is a significant predictor of performance. Excess credit has been shown to be a good predictor of recessions (Borio and Lowe, 2002), and the duration and severity of a recession (Jorda, Schularick and Taylor, 2013). The addition of credit 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 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 FCIs on growth also depend on excess credit, the nonlinear results would be more consistent with models of endogenous risk-taking and amplification of shocks, rather than just the effect of 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.

A main contribution of this paper is to show empirically that the predicted effects of financial conditions on GDP growth and its volatility vary at different projection horizons and are consistent with an intertemporal risk-return tradeoff. 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 that the effect of financial conditions switches over the projection horizon, with looser financial conditions supporting higher GaR in the near-term but lower GaR in the medium-term relative to average financial conditions; GaR is even lower if initial conditions are a credit boom. The term structure of GaR suggests that there is a tradeoff between building greater resilience in normal times in order to reduce downside risks in stress periods (see Adrian and Liang, 2018).

More specifically, our main results are as follows: First, financial conditions have strong forecasting power for the expected distribution of growth. Coefficients on FCI are significant in the short run and the medium run for AEs and EMEs. Importantly, the signs of the coefficients reverse from the short to medium term. By directly estimating both growth and volatility, we show evidence of a strong negative correlation between conditional mean and conditional volatility.

Second, the effects of FCI on the growth distribution for AEs differ in a credit boom than in other situations (when financial conditions are not ultra-loose and the credit gap is not high). A credit boom implies lower growth and higher volatility in the medium-term than when just financial conditions are loose. These results are more consistent with a model of endogenous risk-taking and the volatility paradox than just different adjustment periods to a common shock. In addition, the results are robust to using credit-to-GDP growth as an alternative measure to the credit-to-GDP gap.

Third, our estimates imply meaningful differences in GaR over the projection horizon depending on the initial level of financial conditions. There is a significant difference in the growth distribution between times when the initial FCI is very loose or very tight. For very loose FCI in AEs, conditional growth falls from about 3.0 percent to 2.0 percent (at an annual rate) over horizon quarters 1 to 12, and below the conditional level of 2.5 percent for when initial FCI is at average levels. Correspondingly, GaR (5^{th} percentile) falls from 1.5 percent to 0.5 percent at an annual rate over the projection horizon. For AEs, the estimated GaR values in the third year for an initial credit boom fall to near zero, suggesting the lower 5^{th} percentile of the growth distribution comes close to an outright recession nearly three years out.

For EMEs, conditional growth and GaR for very loose financial conditions also decline over the projection horizon, but the differences in economic performance are less sizable than for the AEs. The less significant tradeoff for EMEs could reflect that the sample period for estimating the model for EMEs is shorter and that financial markets for pricing risks were not as well-developed during parts of the sample period, and thus had less effect on the behavior of financial intermediaries or investors.

Finally, based on preliminary estimations, we obtain qualitatively the same results when using the quantile regression approach of Adrian et al (2016), which we apply to our panels using local projections. The quantile regression approach is semiparametric and allows for more general assumptions about the functional form of the conditional GDP distribution. The comparison suggests the two-step results are robust and is promising for forecasting since the two-step procedure may be easier to incorporate into regular macroeconomic forecasting exercises.

These results have important implications for macroeconomic models and policymaking. We document a strong inverse correlation between growth and volatility, a clear violation of a common assumption in many macrofinancial models that volatility is independent of growth. Both the conditional mean and conditional volatility of GDP growth depend on financial conditions. Financial conditions, in turn, reflect policymaking that targets growth. Hence, models of macrofinancial linkages need to incorporate the endogeneity of first and second moments. Moreover, the covariation of conditional means and conditional volatilities 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, that very loose financial conditions and high GaR can lead to buildups in vulnerabilities that over time result in large downside risks. In aspiration, macroprudential policies would consider both growth and volatility. For example, higher capital requirements could aim to tighten financial conditions which would reduce the risk of bank failure and negative spillovers for the economy in the future.

Monetary policy would also consider growth and volatility, but in practice relies heavily on models that assume volatility and growth are independent. However, our results indicate that certainty equivalence is severely violated. Our results suggest policymakers face tradeoffs between higher short-term growth and larger medium-term risks 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 described above, we build on Adrian, Boyarchenko, and Giannone (2016), who document that financial conditions can forecast downside risks to GDP growth. Other papers look at changes in risk premia and financial conditions and 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)).

In this paper, we focus on the effects of FCIs on the distribution of growth, but we do not explore what determines FCIs. Models depict variations in financial conditions as time-varying risk premia of investors, which may be determined by changes in bank capital constraints (He and Krishnamurthy, 2013), and endogenous reactions of financial intermediaries via value-at-risk (VaR) constraints to periods of low volatility (Brunnermeier and Pedersen (2009), Brunnermeier and Sannikov (2014), and Adrian and Shin (2014)). Or reversals may reflect sentiment-based theories that can provide triggers that lead to recessions and credit busts (Minsky 1977). We leave to future work a more general approach to estimate the term structure of the joint distribution between GDP growth and FCIs.

The rest of this paper is organized as follows. Section 2 presents the stylized model of GDP growth and financial condition, describes the 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, and Section 5 discusses some robustness analyses. Section 6 provides results using the quantile regression method and shows the results for GaR are similar to results from the simpler estimation assuming a Gaussian distribution, suggesting the simpler method is able to capture asymmetries fairly well. Section 7 concludes.

2. Modeling Growth-at-Risk

We use a stylized model of GDP following Adrian, Boyarchenko, and Giannone (2016) who estimate the expected conditional GDP growth distribution based on economic and financial conditions at one-quarter and at four-quarters for the US using quantile regressions. They demonstrate a decline in the conditional median of GDP growth and an increase in the conditional volatility with a deterioration in financial conditions, indicating greater downside risks to growth. They compare results to the heteroskedastic variance model estimated using maximum likelihood methods for the conditional mean and conditional lower and upper 5th percentiles for one quarter ahead. They find the simple heteroskedastic model is able to reproduce the strongly skewed conditional GDP distribution (p. 15).

a. Growth at risk in a heteroskedastic variance model

We expand their framework by estimating the dynamics of GDP growth and volatility over a projection horizon of one to twelve quarters using local projections estimation methods and applying the model to 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 also substantially expand the sample to 21 countries and allow for nonlinearities from vulnerabilities (excess credit).

We model 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. Our baseline empirical model is described by the following two equations:

$$\Delta y_{i,t+h} = \gamma_0^{(h)} + \gamma_{i,1}^{(h)} + \gamma_2^{(h)} x_{i,t} + \gamma_3^{(h)} \Delta y_{i,t} + \gamma_4^{(h)} \pi_{i,t} + \gamma_5^{(h)} \lambda_{i,t} x_{i,t} + \varepsilon_{i,t+h} \quad \text{with } h=1,\ldots,12 \qquad (1)$$

$$\ln \varepsilon_{i,t+h}^2 = \beta_0^{(h)} + \beta_{i,1}^{(h)} + \beta_2^{(h)} x_{i,t} + \beta_3^{(h)} \pi_{i,t} + \beta_4^{(h)} \lambda_{i,t} x_{i,t} + \nu_{i,t+h}\,, \qquad (2)$$

where $\Delta y_{i,t+h}$ is the average GDP growth rate between quarter *t* and *t+h* for country *i*, $x_{i,t}$ is the FCI, $\pi_{i,t}$ is the inflation rate, $\lambda_{i,t}$ is a time varying variable that measures the state of the economy (e.g. the stance of the credit cycle), $\varepsilon_{i,t+h}$ is an heteroskedastic error term that affects the volatility of GDP growth, and $\nu_{i,t+h}$ is an i.i.d. Gaussian error term.

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

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

where $GaR_{i,h}\left(\alpha \middle| \Omega_t\right)$ 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 average growth rate between periods t and $t+h$ given Ω_t (the information set available at t) for a given probability α. Thus, for a low value of α, GaR will capture the expected growth at the lower end of the GDP growth distribution. We focus on a GaR measure at the lower 5th percentile of the GDP growth distribution.

Our empirical model in (1) and (2) aims to capture the dynamics following a loosening of financial conditions, and to test whether the immediate benign growth conditions are sustainable or if volatility rises more sharply in the medium term, and allowing for nonlinearities. 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 leverage, 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.

Equations (1) and (2) 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. Equation (1) 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.

We incorporate the state of the credit cycle $\lambda_{i,t}$ to capture nonlinearities that could occur from a negative shock 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 a financial vulnerability, which could lead to fire sales by constrained intermediaries or to debt overhang that impedes efficient adjustments to lower prices. We use the private nonfinancial credit-to-GDP gap, 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. 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 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 expansions do not have independent effects on economic performance; instead, the contractions that follow credit expansion reflect monetary policy and financial conditions.

To incorporate amplification channels, we define the state of the economy $\lambda_{i,t}$ as a dummy variable that captures the buoyancy of financial markets as follows:

$$\lambda_{i,t} = \begin{cases} 1 & \text{if } x_{i.t} \geq \bar{x}_{i,t} \text{and } \; CreditGap > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{4}$$

That is, in states where FCIs are above their historical average and the credit gap is positive, $\lambda_{i,t}$ takes a value of 1. In all other states $\lambda_{i,t}$ takes a value of zero. We measure the credit gap by applying an HP filter to nonfinancial private credit as a percent of GDP and using a smoothing coefficient of 40000, as recommended by BIS. We then define the credit boom as the top half of observations of $\lambda_{i,t}$ =1 in terms of highest FCI and highest credit gap.

The credit boom is added as an interaction with FCI in (1) and (2) to test whether looser financial conditions have different effects on future growth distribution when the credit-to-GDP gap is high. 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 higher expected growth in the near-term but higher downside risk to GDP, lower GaR, in the medium-term.

b. Model estimation

Our baseline empirical model is described by equations (1) and (2). Equation (1) captures the effects of FCIs on the conditional mean of GDP growth over different time horizons *h,* and equation (2) captures the effect of FCIs on the conditional variance. 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. For simplicity, we estimate the model in two-steps: we use the residuals from the estimated first equation and regress $\ln \varepsilon_{i,t+h}^2$ onto the right-hand side variables of equation (2).[2]

We use the average of cumulative growth rates to make it easier to interpret the units in equations (1) and (2), rather than cumulative growth rates often used in other applications of the local projection method.[3] This gives us an estimated average treatment effect of a change in FCI on GDP growth and GDP growth volatility. 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).

We use a two-step panel estimation approach to measure the forecasting role of FCIs on the distribution of GDP growth. We first estimate the relationship between the change in output, financial conditions, and the other variables. From this equation we extract the estimated variance of the change in output, which we regress on financial conditions in a second step. This two-equation empirical model assumes a *conditionally* Gaussian distribution with

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

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

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.

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 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 each h) for a set of 11 AEs and a set of 10 EMEs, in panel regressions with fixed effects. The estimated parameters on FCIs and the other independent variables represent average behavior across each set of countries.

3. Data

Quarterly data for real GDP growth and consumer price indexes 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 [xx] of world GDP in 2016.

The FCIs for the 21 countries are from the IMF October 2017 Global Financial Stability Report, Chapter 3. The underlying variables and construction are described in the appendix to Chapter 3. FCIs are a parsimonious way to summarize the information in asset prices and credit. The FCIs used in this study reflect domestic and global financial factors that influence a country's financial conditions, and are based on up to 19 variables.[5] An important advantage of these FCIs is that they have been constructed on a consistent basis for a long sample time period and across a large number of countries.

[4] See Jorda (2005) and Stock and Watson (2007).

[5] The construction differs from a principal components approach, which maximizes the common variance among variables, by also using its ability to discriminate one-year-ahead growth below the 20th percentile of historical outcomes. That is, the FCI is designed to distinguish between periods of low GDP growth and normal GDP growth.

Credit-to-GDP ratios are from the BIS, and credit is nonfinancial credit to households and businesses. The credit-to-GDP gap is the ratio less its long-run trend, which is based on BIS estimations with a Hodrick-Prescott filter with smoothing coefficient equal to 400,000. Because these estimates may not represent true underlying trends, we also use the growth in the credit-to-GDP ratio over a moving four-year window in some estimations below as an alternative to the gap.

Summary statistics for the panel of AEs and for the panel of EMEs are presented in Table 1. The data for most of the 11 AEs begin in 1973, and data for most of the 10 EMEs begin in 1996. Most of the advanced economies have data for the full sample period 1973 to 2016, but data for Japan start in 1975:q2, France 1980:q3, and Spain in 1980:q4. Most of the emerging market economies have data for the full sample period 1996 to 2016, but data for Turkey start in 1996:q3, Russia 2006:q1, and Brazil 2006:q4. The values in the tables are averages across countries and across time, for 11 AEs and 10 EMEs.

[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 quarterly growth is 0.56 percent in AEs, and 1.08 percent in EMEs. Inflation in the AEs is much lower than in the EMEs, 3.6 percent and 8.2 percent annual rate.

For both AEs and EMEs, FCIs have a high standard deviation, consistent with financial conditions that oscillate frequently around their average. The standard deviation of the credit-to-GDP gap is much larger in the EMEs than in the AEs. Credit-to-GDP growth (measured over the past four years) averages 9.7 percent in EMEs, and 6.9 percent in AEs, which reflects greater variation across countries (more so than over time) as the EMEs in our sample are at different stages of financial deepening. Periods when financial markets are buoyant ($\lambda_{i,t} = 1$) —when FCIs are looser than average and the credit gap is positive—represent about 28 percent of quarters in the AEs and 29 percent in EMEs. Such periods are not the norm, but are a significant fraction. We focus instead a tighter definition for a credit boom, which is defined by the top half of the observations for $\lambda_{i,t}$ equals 1, since buoyant conditions defined by just above average likely do not suggest high risk of greatly amplified negative shocks.

In general, the data show that FCIs tend to track more frequent business cycles and are more volatile than credit-to-GDP gaps, which are slower moving. Charts of FCI and credit-to-GDP gap for all of the 21 countries in our sample are in Appendix A, and Figures 3 and 4 highlight a few countries (US, Japan, Chile, Mexico). The FCI is at its tightest level for many countries, including the US, in 2008, when VIX, a global indicator of risk, rose to record levels. This was not the case in four other AEs: Financial conditions were tighter in the mid-1970s than in 2008 in Japan, Spain, and Italy, and tightest in France in the early 1980s. And while many countries were in a build-up phase of the credit-to-GDP gap in 2008, many had peaks earlier in the 1980s. Among EMEs, while two countries (Indonesia and South Africa) followed the US pattern with a peak in 2008, credit-to-GDP gaps peaked in the early 2000s for Chile and in the mid-1990s for Mexico. 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.

[Figures 3 and 4 HERE]

The relative persistence of the right-hand side variables helps to understand the dynamics of GDP growth. The vulnerability, credit gap, is a slow-moving variable, which can take many years to build up. The price of risk, FCI, is a much faster moving variable which can tighten rapidly.

4. Empirical Results

a. **Estimated FCI coefficients, baseline and with interaction.**

Figures 1 and 2 shown above are the estimated coefficients on FCI in a specification without an interaction term with credit boom. FCI is transformed so that higher FCI represents looser financial conditions (higher asset prices, lower price of risk. As discussed above, coefficients for growth are positive in the near-term, and become negative in quarters further out, and coefficients for volatility are negative in the near-term, and become positive in quarters further out. They provide strong empirical support for an intertemporal tradeoff of loose financial conditions and benign economic conditions, which sets the stage for a deterioration in performance three years later.

Figures 5 and 6 show the model estimation results with the interaction term (FCI*credit boom). The coefficients on FCI in credit boom periods (shown by boom=1) are generally significant, as are the coefficients on FCIs in other periods (which are either a credit bust or average conditions). Recall that credit boom periods represent 14.0 percent of the sample in the AE panel and 14.7 percent in the EME panel. In the AE estimations, the coefficients on FCI in the credit boom have the same contour as the coefficients in other periods over the projection horizon, but some of the coefficient estimates differ in magnitude. By the third year out, the interaction effect of looser initial financial conditions on growth has a statistically significant larger negative effect on growth, and a significantly greater increase in volatility. These results suggest that in AEs, initial credit boom conditions can be more costly than when only initial financial conditions are loose.

For the EMEs, the estimated coefficients for FCI in a credit boom period are significant and positive for growth, and do not forecast negative growth within the projection horizon. However, the coefficients for FCI on growth for other periods (non-credit boom) continue to indicate a decline in growth and higher volatility in the medium run. The credit boom interaction suggests that credit booms do not play the same role in EMEs as in AEs. Still, the results for EMEs remain highly supportive of an intertemporal tradeoff of loose financial conditions for higher current growth and low volatility and lower growth and higher volatility later.

[Figures 5 and 6 HERE]

These results 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 the credit gap is high. The higher costs in the medium term estimated for credit boom 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. **Conditional Mean and Growth at Risk**

We now build on the coefficient estimates for equations (1) and (2) and provide estimates of the conditional GDP distribution. We show first that financial conditions have a meaningful effect on conditional GDP mean growth and volatility. We then show that credit boom can have a meaningful effect on GaR

GaR measures the expected conditional growth in the lower (left) tail of GDP growth distribution.[6] Thus, it captures the level of expected GDP growth for which there is a given probability that growth will fall to that level. Equation (5) shows GaR from Equation (3) is computed as:[7]

$$GaR_{i,t+h}(\alpha) = E\left(\Delta y_{i,t+h} \mid \Omega_t\right) + N^{-1}(\alpha) Vol\left(\Delta y_{i,t+h} \mid \Omega_t\right) \tag{5}$$

where $GaR_{i,h}(\alpha)$ is growth at risk for country *i* in *t+h* quarters in the future at a α 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 Ω_t available at *t* obtained by fitting equation (1). $Vol\left(\Delta y_{i,t+h} \mid \Omega_t\right)$ is the expected volatility at period $t+h$, which is equal to the squared root of the exponent of the fitted value for equation (2). $N^{-1}(\alpha)$ denotes the inverse standard normal cumulative probability function at a probability level α . In what follows α is fixed at 5%, thus capturing the left tail of GDP growth in the 5th percentile of its conditional distribution.

Figure 7 shows the time series of average GaR estimates (averaged across countries), expressed at an annual rate, for a projection horizon of 4 quarters for AEs and for EMEs. Lower values of GaR indicate low growth is more likely. The figures also plot the average conditional mean and the actual growth rate (average cumulative growth from period t to t+4).

[Figure 7 HERE]

As shown for the AEs and EMEs, the average conditional mean and average GaR tend to lead realized growth. Moreover, conditional means and volatility are negatively correlated, so lower projected growth is associated with higher volatility and lower GaR.

c. **Term structure of conditional means and GaR by initial FCI**

The implications of the estimated coefficients and the main empirical results for the intertemporal tradeoff can be illustrated by the term structures for the conditional mean and GaR, sorted by the initial FCI. We show these estimates based on initial FCI, in the top decile (very loose financial conditions), in the bottom

[6] Given the assumption of a conditional Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth. Our results appear to be robust to using a semi-parametric quantile regression estimator of Adrian et al (2016), as shown in section 6.

[7] 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.

decile (very tight financial conditions), and the middle 60 percent, for h=1 to 12 (figures 8 and 9). We also show the conditional mean and GaR for initial credit boom conditions. While this group overlaps with the top decile based on FCI, the additional restriction that the credit gap is high allows us to evaluate nonlinearities when vulnerabilities are high.

[Figures 8 and 9 HERE]

The estimated conditional means from the model suggest sharp differences based on initial financial conditions. Very loose FCIs (top decile) are associated with a higher and tighter distribution of growth relative to average FCIs for up to five and six quarters out. The conditional expected growth (annual rate) for very loose FCIs is 3 percent, more than 50 basis points higher than for the average FCI in the first quarter, and still 20 basis points higher in the fourth quarter. GaR also is much higher, suggesting much lower downside risk in the near-term. However, conditional expected growth for the top decile falls notably over the projection horizon, to roughly 2.0 percent in the third year, and is lower than if initial financial conditions had been average, at about 2.4 percent. GaR for the top decile also falls significantly and is substantially lower than for average financial conditions in the third year. These indicate meaningful tradeoffs for growth and volatility.

The estimates for when initial conditions reflect an exuberant credit boom illustrate the role of credit as a vulnerability. In the near-term, looser financial conditions when the credit gap is already positive (blue line) do not have as large a positive effect on growth as when the credit gap is not necessarily positive (red line). This result could reflect that when borrowers are already stretched, looser conditions do not lead borrowers to take on as much additional credit as if they were below their trend borrowing. At the same time, GaR is lower, suggesting greater downside risks. Over the projection horizon, conditional growth falls and is quickly below growth when initial financial conditions are average, and by the third year, the average difference of [80 basis points] is substantial. Moreover, the GaR is also lower than the GaR for initial average FCI, by almost 1 percentage point, and the level hovers just above zero, putting greater weight on the probability of a recession.

These results imply a significant tradeoff for policymakers. Looser financial conditions are associated with higher conditional growth and lower volatility in the near-term, but lower conditional growth and higher volatility in the medium-term. When there is a credit boom, even looser conditions make the tradeoff worse. In this case, looser conditions provide only modest benefits in the near-term but a substantial reduction in growth and higher probability of a recession in the medium-term.

The estimates also show that the worst outcomes in the short run are when FCIs are initially extremely tight, in the lowest decile. Conditional growth and GaR are very low, suggesting a deep recession or a financial crisis. However, these effects dissipate over time and converge to conditions for initial average financial conditions in the medium run. The results also show that financial conditions that are moderate deliver higher growth on average with less downside risk. What determines initial financial conditions is outside this empirical model and further work is needed to model financial conditions. But results are suggestive: lower GaR in the medium run associated with initial credit booms than with initial moderate financial conditions suggest that policymakers should try to avoid build-ups in macrofinancial imbalances that could amplify negative shocks and lead to substantial downside deviations in financial conditions.

For EMEs, the effects of looser financial conditions in the near-term on growth and GaR are qualitatively very similar to the effects found for the AEs (figure 9). Looser financial conditions are associated with higher growth and higher GaR in the short run, and the benefits of looser conditions are diminished somewhat if the credit gap is already positive. However, unlike the experience in the AEs, there does not seem to be a significant intertemporal tradeoff in which very loose financial conditions or a credit boom leads to below average performance in the medium-term. We plan to explore more the estimations for the EMEs. As noted above, relative to the AEs, the data are available for a shorter sample period, financial markets may have been less significant for pricing risks for much of that time, estimations of the credit gap may be more subject to error because there is less financial deepening, and there may be wider variation across countries in this sample because they are less globally integrated.

5. Robustness

We evaluate the robustness of the results with three extensions, and then also present estimates of the conditional growth distribution using a semi-parametric panel quantile regressions (section 6).

In the first of three extensions, we substitute credit growth for the credit gap. The credit-to-GDP gap has been suggested by the BIS as a good measure of financial vulnerability, as it has been found to be a good predictor of a recession in cross-country studies. However, it has been criticized for relying on an estimated long-run trend. Credit growth, measured by the growth in credit-to-GDP over the past four years, is an alternative. We use credit growth in place of credit-to-GDP gap when defining a credit boom. Results for both AEs and EMEs are very similar (figure 10).

In a second, we estimate the model as a SUR system, rather than a panel with fixed effect. The FCI coefficients by country from a SUR estimation are shown in figure 11. While the model estimates do not show that that every country on its own follows the panel estimates, the downward trend for the mean and the upward trend for volatility appears to show through.

We also plan to evaluate vulnerability measures other than credit. Empirically, we are constrained by the lack of comparable data across countries over long periods of time, but we plan to test growth of bank assets. In preliminary estimations, we used external debt-to-GDP rather than credit-to-GDP for EMEs. The results with external debt are similar to those based on credit, suggesting that the less significant results for EMEs are not being driven by that credit gaps may not be important for macroeconomic performance in those countries.

6. An Alternative Estimation Method – Quantile Regressions

There are significant advantages to using the two-step conditional heteroskedastic model procedure of equations (1) and (2) to estimate the distribution of growth. Quantile regressions do not make distributional assumptions, allowing for more general modeling of the functional form of the conditional GDP distribution. We follow Adrian, Boyarchenko, Giannone (2016) and map the quantile regression estimates into a skewed t-distribution. The skewed t-distribution allows for four time-varying moments, hence capture not only time variation in the conditional mean and volatility, but also the conditional skewness and kurtosis. In this section, we compare the results from our two-step Gaussian estimator to results from preliminary quantile regression estimates for the panel. We show below that the two-step procedure for estimating the mean and variance assuming an unconditional Gaussian distribution to capture adequately the term structure of GaR and the conditional distribution.

The panel quantile regressions are estimated as in Adrian et al (2016). The estimates of the conditional predictive distribution for GDP growth rely on quantile regressions. Let us denote $\Delta y_{i,t+h}$ the annualized average growth rate of GDP for country *i* between *t* and *t*+*h* and by $x_{i,t}$ a vector containing the conditioning variables. In a panel quantile regression of $\Delta y_{i,t+h}$ on x_t the regression slope δ_α is chosen to minimize the quantile weighted absolute value of errors:

$$\hat{\delta}_{\alpha} = \underset{\delta_{\alpha} \in \mathbb{R}^{k}}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(\alpha \cdot 1_{\Delta y_{i,t+h} > x_{i,t}\delta} \left| \Delta y_{i,t+h} - x_{i,t}\delta_{\alpha} \right| + (1-\alpha) 1_{\Delta y_{i,t+h} < x_{i,t}\delta} \left| \Delta y_{i,t+h} - x_{i,t}\delta_{\alpha} \right| \right) \qquad (6)$$

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

$$\hat{Q}_{y_{t+h}|x_{t}}(\alpha) = x_{t}\hat{\delta}_{\alpha} \qquad (7)$$

As in Adrian et al (2016) we fit the skewed *t*-distribution developed by Azzalini and Capitaion (2003) in order to smooth the quantile function and recover a probability density function:

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

Where $dT(\bullet)$ and $T(\bullet)$ 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 shape θ.

We estimate GDP growth between *t* and *t+h* on conditioning variables FCI, lagged GDP growth, and inflation, including a constant.

To summarize the quantile regression results, which are preliminary, we calculate the conditional mean and GaR for AEs and EMEs, sorted by initial FCI. The model estimates are from the baseline specification for each panel, without an interaction for credit boom. They are not estimated yet with fixed effects. Also, we have not yet estimated standard errors for the coefficients in the quantile regressions.

We show the term structure of conditional growth for different initial financial conditions in figures 12 and 13; these figures are the counterparts to figures 8 and 9 based on equations (1) and (2). They are calculated setting initial inflation and lagged growth to sample averages, and do not include fixed effects for countries. They are based on level of initial financial conditions, top decile for very loose, bottom decile for very tight, and the middle approximated by the 20 to 80 percent range. The results exhibit the same strong intertemporal relationship as found with estimations based on Gaussian assumptions: for very loose financial conditions, the median of conditional growth is high in the near term, but falls substantially over the twelve-quarter horizon. For very tight conditions, defined by the upper boundary of the lower decile, conditional growth is low in the near term and rises substantially. GaR estimates from the quantiles conditional on initial conditions also follow the same pattern as from the Guassian estimations. While these results are still preliminary, the same strong empirical relationships between conditional mean and volatility and the inter-temporal tradeoff emerge.

More work is needed to evaluate standard errors, to add an interaction to reflect a credit boom, and then to evaluate the magnitude of the size of the tradeoffs. For example, current estimates shown are evaluated at the boundary of the cutoff for the quantiles, but the average within the categories for the Gaussian, which may affect the magnitudes of the estimated tradeoff. The addition of fixed effects may introduce greater variation in the levels of the means and GaRs if different countries are represented more in the different deciles.

7. Conclusion

Since the global financial crisis and consequent damage to economic growth, economists have focused on exploring linkages between the financial sector and real economic activity. In this paper, we explore the empirical relationship between the financial sector and the distribution of real GDP growth using data for 21 countries. The financial sector is summarized by financial conditions, which reflects the price of risk and financial vulnerabilities that could amplify changes in the price of risk. The relationships we examine are rooted in macrofinancial linkages arising from financial frictions, such as asymmetric information and regulatory constraints, which can create spillovers and contagion. We employ a model of output growth that depends on financial conditions, economic conditions, and inflation, and heteroskedastic variance. This method generates distributions of expected growth and a lower 5th percentile of expected growth for horizons out to twelve quarters, which measures the term structure of growth-at-risk.

Overall, looser financial conditions imply higher growth and lower volatility in the near-term, but these effects reverse in the medium-term and point to greater downside risk. Our estimates indicate that the magnitude of the tradeoff for GaR is substantial for the advanced economies, but is somewhat less significant for emerging market economies. The latter results might reflect the shorter sample, and potential greater heterogeneity across economies.

These empirical results have implications for macroeconomic forecasting and policymaking. The strong inverse correlation between conditional growth and conditional volatility that we document is often ignored in dynamic macroeconomic models, which implicitly assume 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, which 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.

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Table 1. Independent variables

a. Advanced economies

Variables	Mean	Std_dev	Median	10 th	90 th	N
Quarterly Growth Rate	0.0056	0.0091	0.0060	-0.0040	0.0151	1718
Inflation Rate	3.4796	3.4888	2.5509	0.1382	8.4618	1718
Transformed FCI	0.0691	0.9906	0.0987	-1.1195	1.3708	1718
Lambda	0.2794	0.4488	0.0000	0.0000	1.0000	1718
Boom	0.1397	0.3468	0.0000	0.0000	1.0000	1718
Interact with Boom	0.1952	0.5311	0.0000	0.0000	1.0253	1718
credit-to-GDP gap	0.0141	0.1078	0.0140	-0.1040	0.1310	1718
Credit Growth	0.0659	0.1081	0.0604	-0.0676	0.2003	1718

b. Emerging market economies

Variables	Mean	Std_dev	Median	10 th	90 th	N
Quarterly Growth Rate	0.0110	0.0149	0.0117	-0.0033	0.0263	741
Inflation Rate	7.3096	9.5383	5.0880	1.5814	11.6916	741
Transformed FCI	0.0327	1.1058	-0.0745	-1.1818	1.5560	741
Lambda	0.2874	0.4529	0.0000	0.0000	1.0000	741
Boom	0.1430	0.3504	0.0000	0.0000	1.0000	741
Interact with Boom	0.2151	0.5491	0.0000	0.0000	1.2647	741
credit-to-GDP gap	0.0153	0.1026	0.0240	-0.1160	0.1250	741
Credit Growth	0.1009	0.2549	0.1222	-0.1330	0.3632	741

Note. Table includes descriptive statistics for the independent variables for regressions (1) and (2) 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 2016, but data for Japan start in 1975:q2, France 1980:q3, and Spain in 1980:q4. Most of the emerging market economies have data for the full sample period 1996 to 2016, but data for Turkey start in 1996:q3, Russia 2006:q1, and Brazil 2006:q4.

Figure 3. FCI and Credit-to-GDP gap, Advanced economies

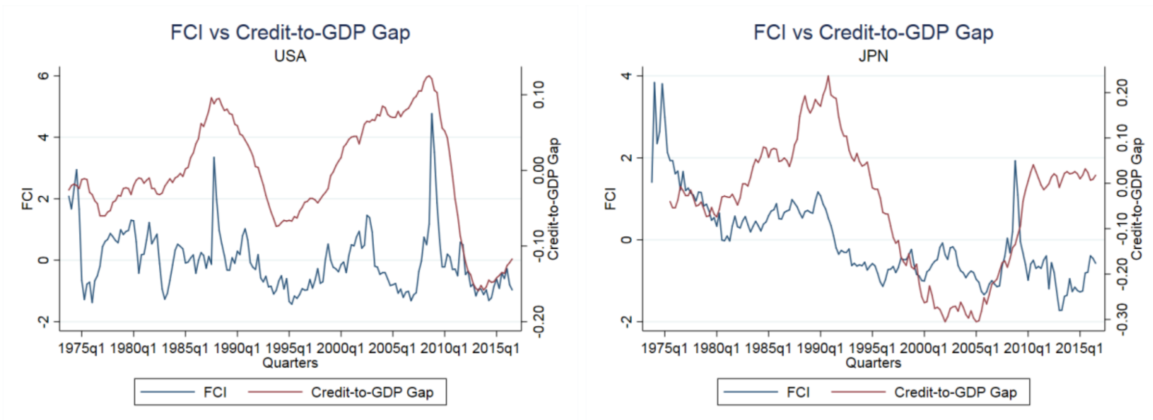
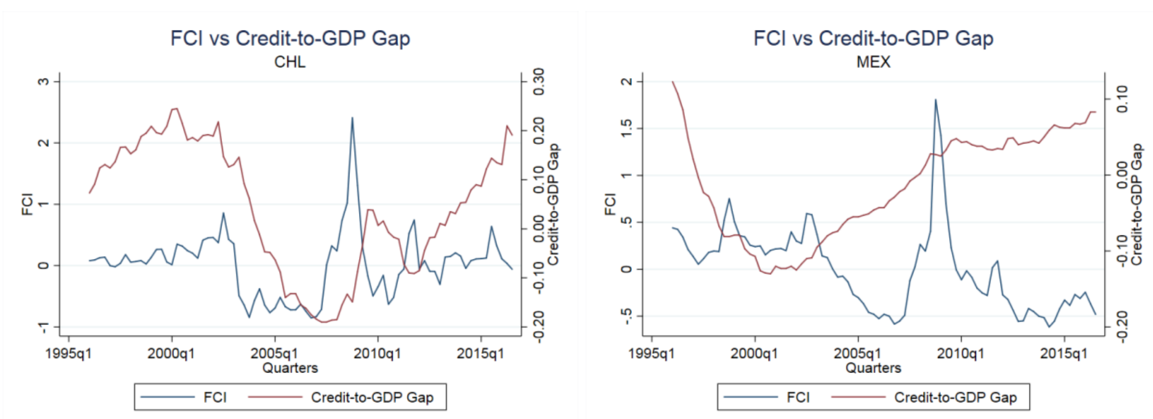


Figure 4. FCI and Credit-to-GDP gap, Emerging market economies



Note. Figures 3 and 4 plot the financial conditions index (FCI, not transformed, where higher values signify tighter financial conditions) and the credit-to-GDP gap for four countries. The FCI is from the IMF Global Financial Stability Report, Chapter 3, October 2017. The credit-to-GDP gap is defined by BIS and available at https://www.bis.org/statistics/c_gaps.htm

Figure 5. Coefficient estimates on FCI, with interaction, Advanced Economies

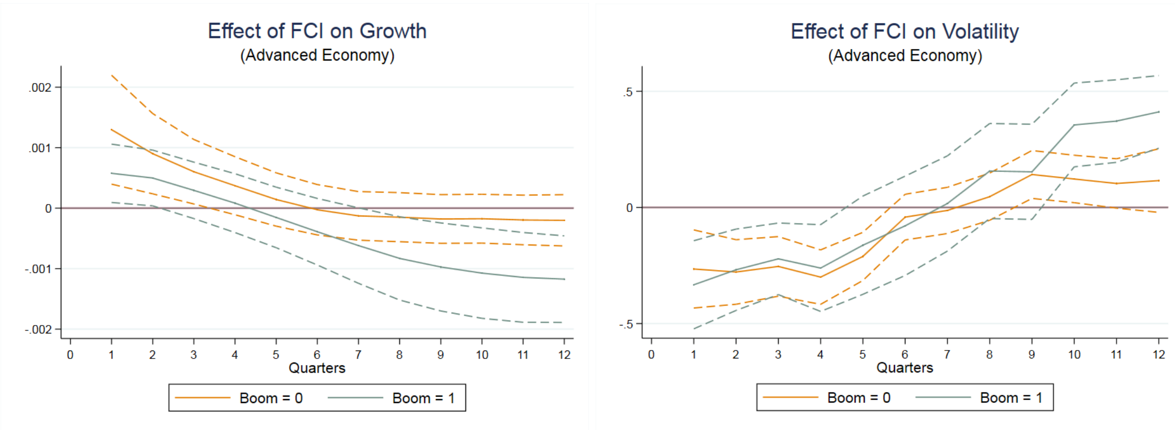
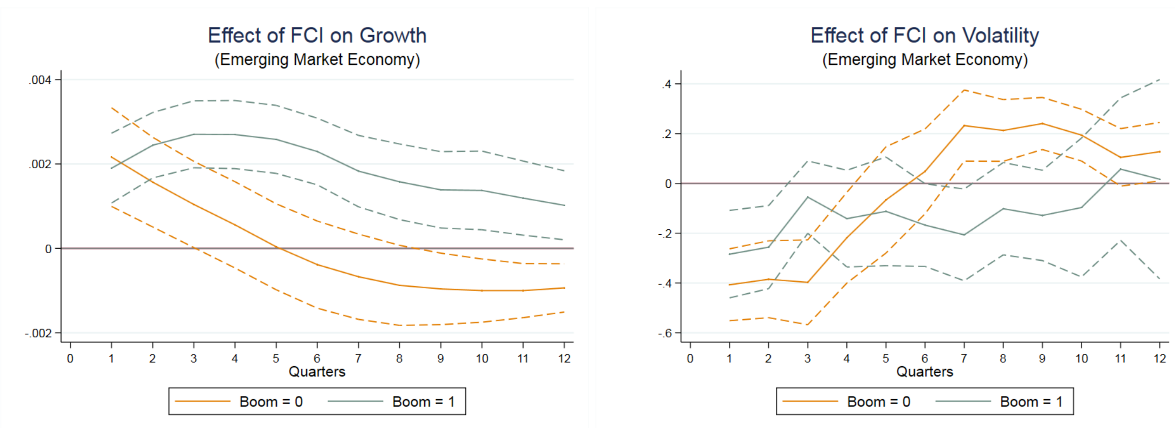
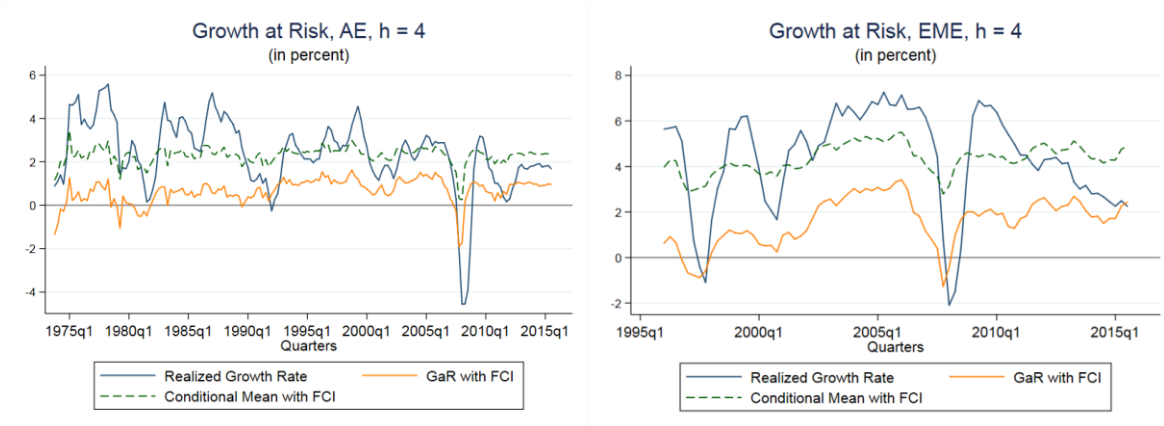


Figure 6. Coefficient estimates on FCI, with interaction, Emerging Market Economies



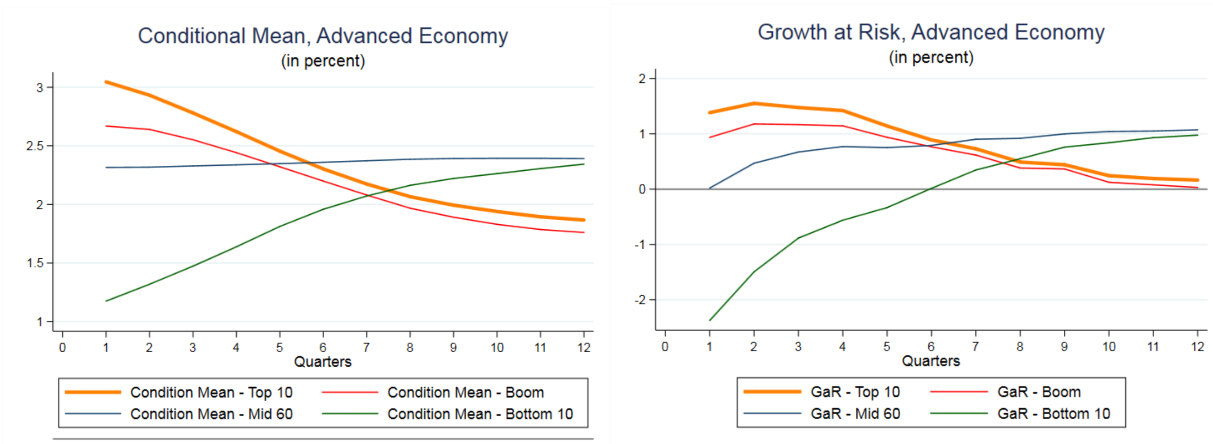
Note: Figures 5 and 6 plot the estimated coefficients on the financial conditions index (FCI) and on its interaction with credit boom on GDP growth and GDP volatility from one to 12 quarters into the future. Higher FCI represents looser financial conditions. Estimates are based on local projection estimation methods, and standard errors are robust to heteroskedasticity and autocorrelation. Advanced economies (AEs) include 11 countries with data for most from 1973-2016. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2016.

Figure 7. Average Conditional Mean and Average Growth at Risk



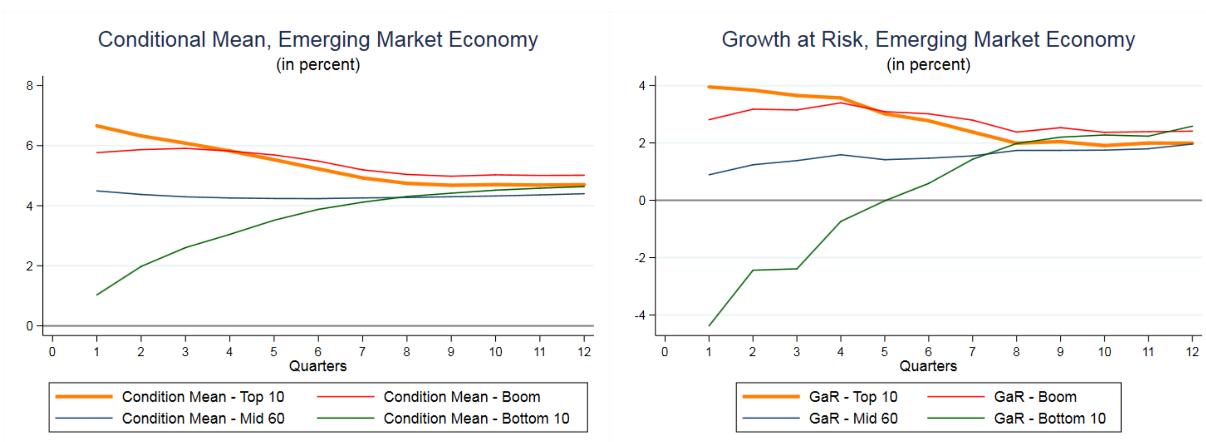
Note. Figures plot the projected average conditional mean growth and average growth-at-risk (expected growth at the 5th percentile) at an annual rate, averaged across countries, from estimations of the distribution of growth. Estimates are based on local projection estimation methods, and standard errors are robust to heteroskedasticity and autocorrelation. Advanced economies include 11 countries with data for most from 1973 to 2016, and emerging market economies include 10 countries with data for most from 1996 to 2016.

Figure 8. Term structures of conditional mean and GaR by initial FCI, AEs



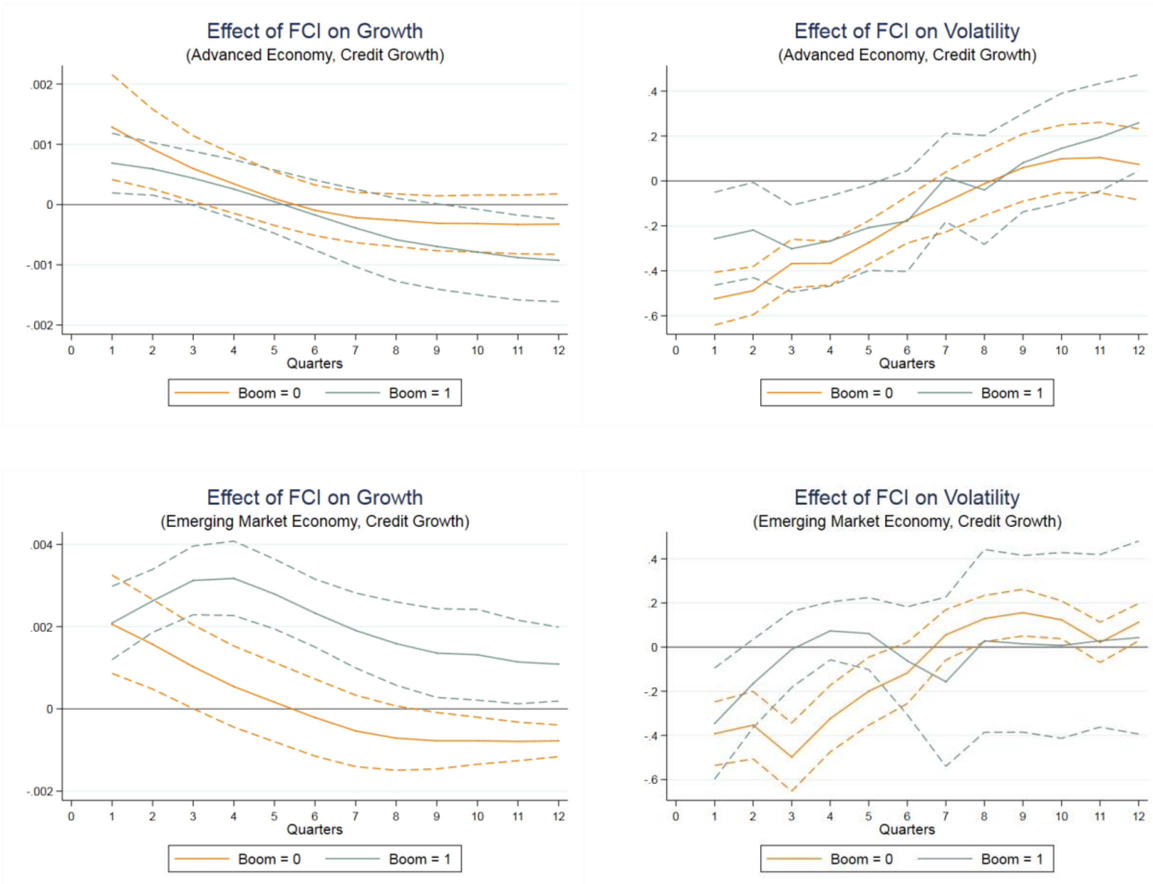
Note. Figures plot the projected conditional mean growth and growth-at-risk (expected growth at the 5th percentile), at an annual rate, based on estimations of the distribution of growth. The conditional mean and growth-at-risk projections are sorted on initial financial conditions, for the top decile, bottom decile, a middle range, and credit boom. 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 2016.

Figure 9. Term structures of conditional mean and GaR by initial FCI, EMEs



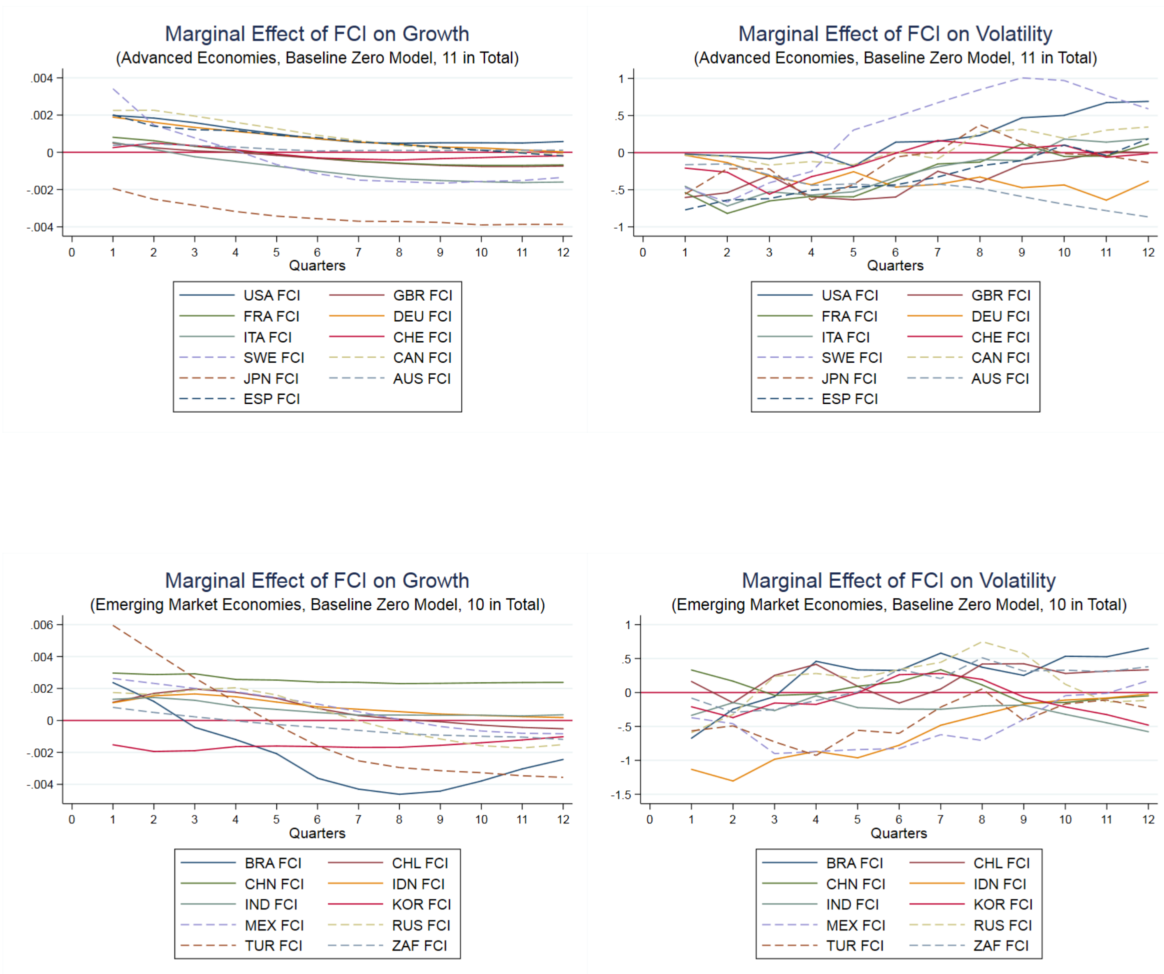
Note. Figures plot the projected conditional mean growth and growth-at-risk (expected growth at the 5th percentile), at an annual rate, based on estimations of the distribution of growth. The conditional mean and growth-at-risk projections are sorted on initial financial conditions, for the top decile, bottom decile, a middle range, and credit boom. 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. Emerging market economies include 10 countries with data for most from 1996 to 2016.

Figure 10. Coefficient estimates on FCI, with credit growth instead of credit gap



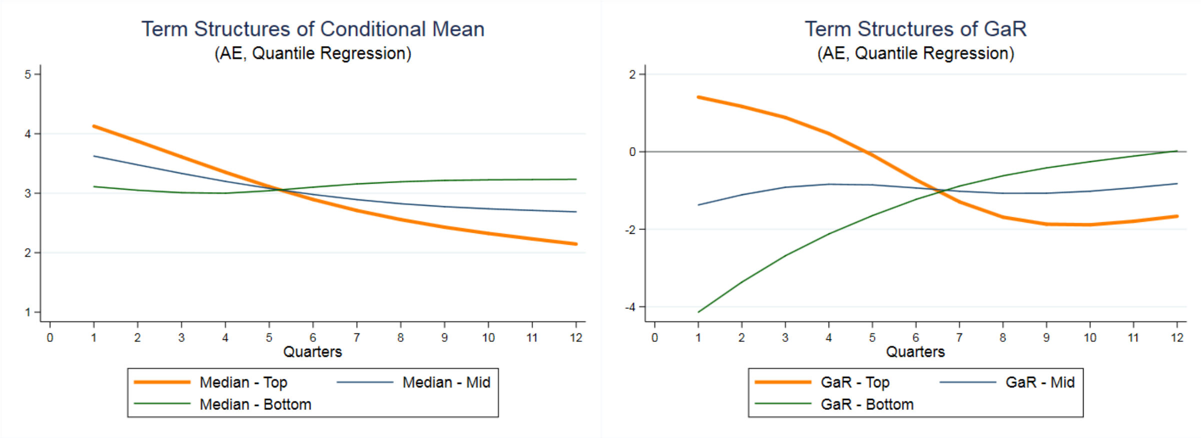
Note: Figures plot the estimated coefficients on the financial conditions index (FCI) and on its interaction with credit boom on GDP growth and GDP volatility from one to 12 quarters into the future. Credit boom is defined based on high credit growth as an alternative to a high credit gap. Higher FCI represents 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 1973-2016. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2016.

Figure 11. Coefficient estimates on FCI from Seemingly Unrelated Regressions



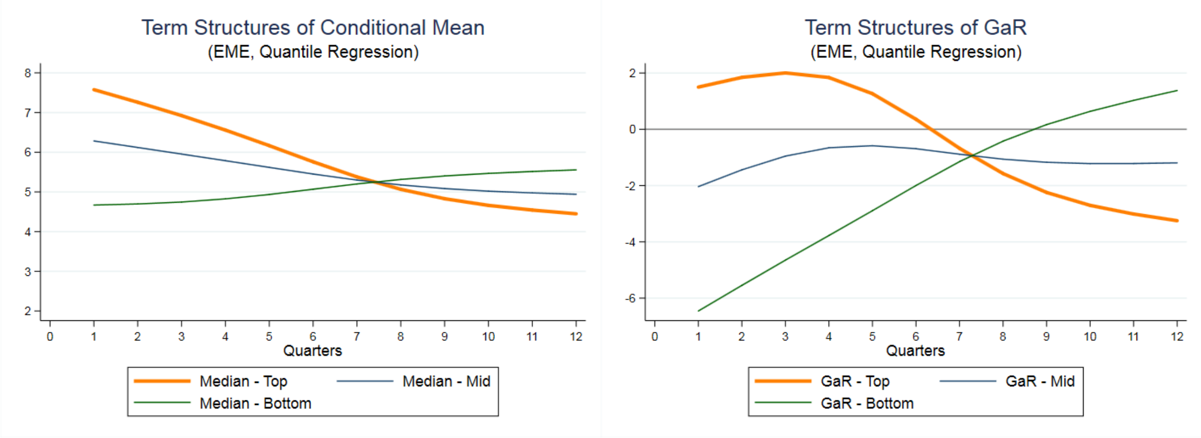
Note: Figures plot the estimated coefficients on the financial conditions index (FCI) on GDP growth and GDP volatility from one to 12 quarters into the future. Higher FCI represents looser financial conditions. Estimates are based on local projection estimation methods, and standard errors are robust to heteroskedasticity and autocorrelation. Advanced economies (AEs) include 11 countries with data for most from 1973-2016. Emerging market economies (EMEs) include 10 countries with data for most from 1996 to 2016.

Figure 12. Term structures of median and GaR from quantile regressions, by initial FCI, AEs



Note. Figures plot the projected conditional mean growth and growth-at-risk (expected growth at the 5th percentile), at an annual rate, based on estimations of the distribution of growth with the FCI, using quantile regressions. The conditional mean and growth-at-risk projections are sorted on initial financial conditions, for the top decile, bottom decile, a middle range, and credit boom. Higher values of FCI represent looser financial conditions. Projected values are based on average initial values for inflation and lagged growth, and do not include fixed effects. Advanced economies include 11 countries with data for most from 1973 to 2016.

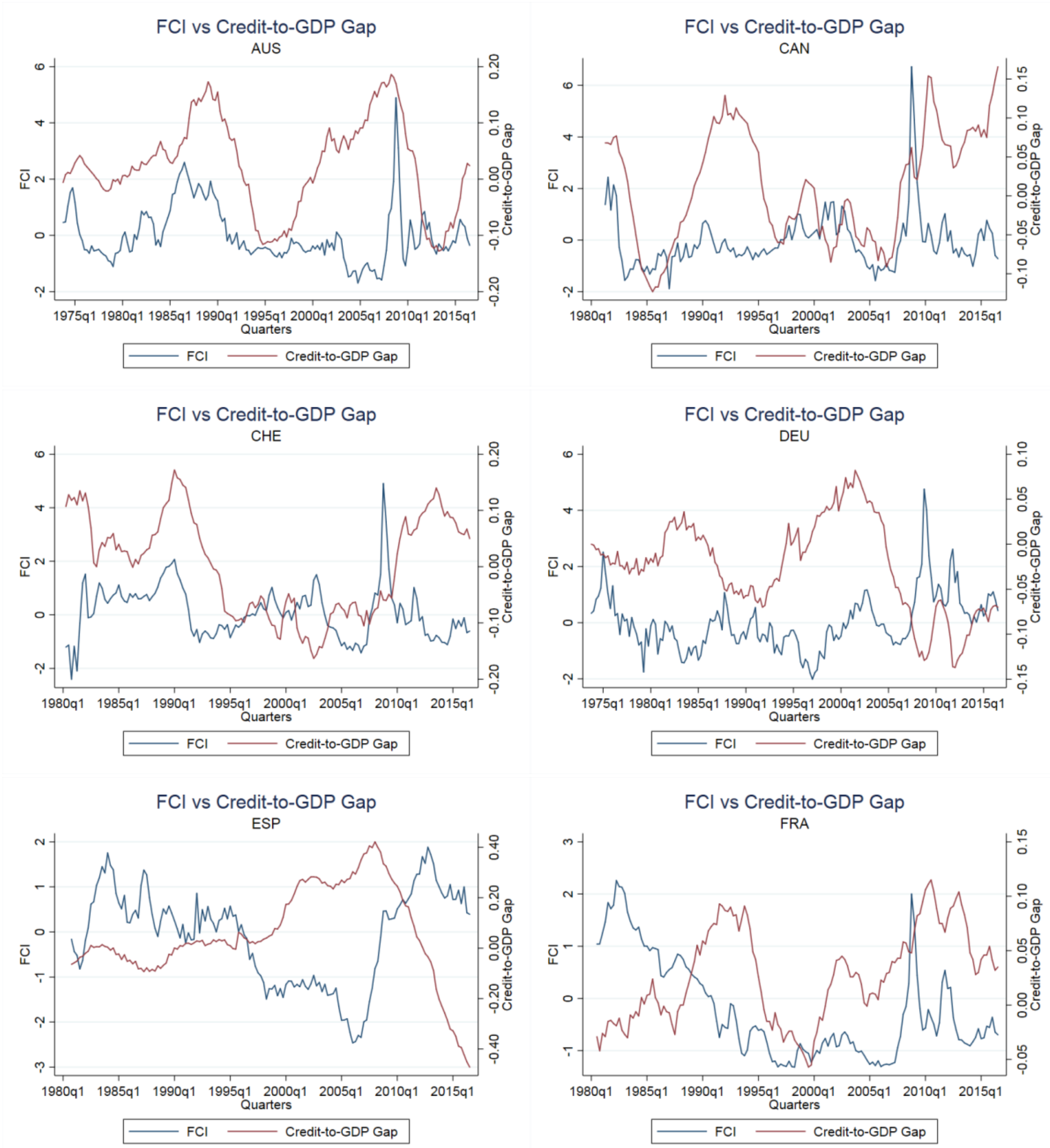
Figure 13. Term structures of median and GaR from quantile regressions, by initial FCI, EMEs

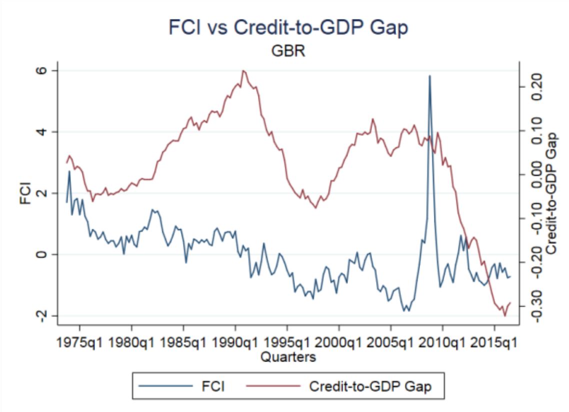


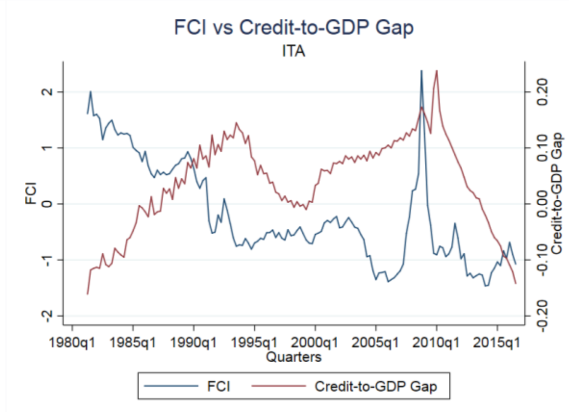
Note. Figures plot the projected conditional mean growth and growth-at-risk (expected growth at the 5th percentile), at an annual rate, based on estimations of the distribution of growth with the FCI, using quantile regressions. The conditional mean and growth-at-risk projections are sorted on initial financial conditions, for the top decile, bottom decile, a middle range, and credit boom. Higher values of FCI represent looser financial conditions. Projected values are based on average initial values for inflation and lagged growth, and do not include fixed effects. Emerging market economies include 10 countries with data for most from 1996 to 2016.

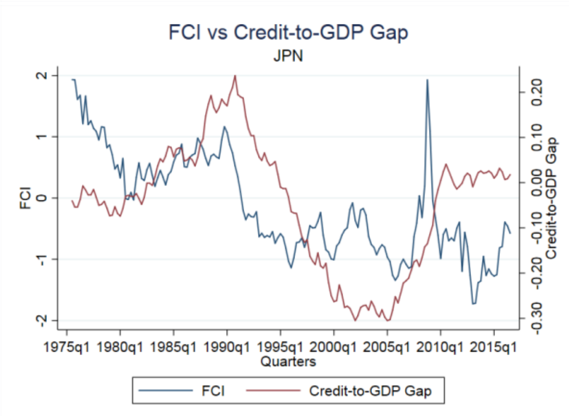
Appendix A: FCI and Credit-to-GDP gap

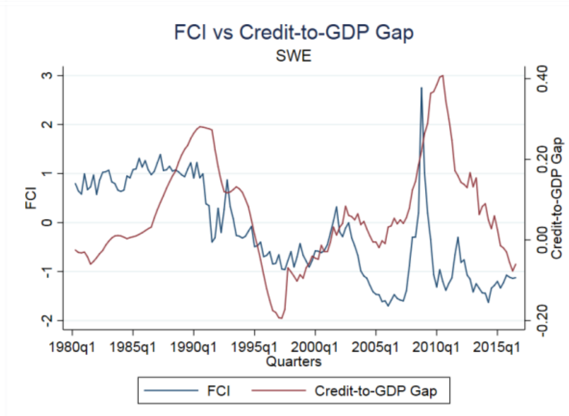
a. Advanced economies

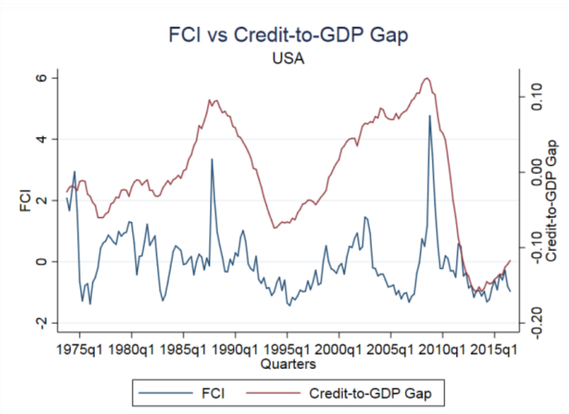



FCI vs Credit-to-GDP Gap
GBR
FCI
Credit-to-GDP Gap
Quarters
1975q1 1980q1 1985q1 1990q1 1995q1 2000q1 2005q1 2010q1 2015q1
FCI
Credit-to-GDP Gap

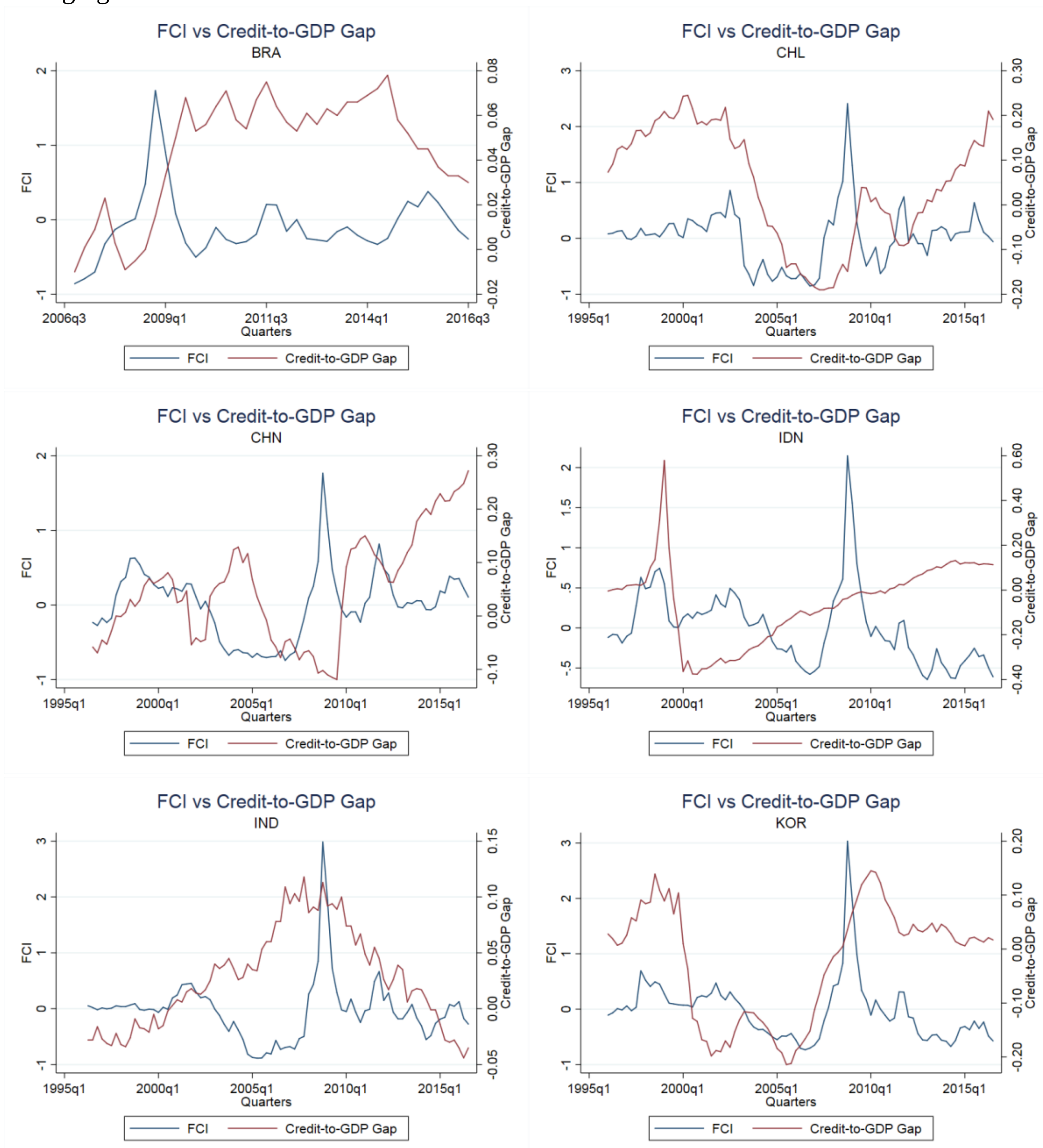

FCI vs Credit-to-GDP Gap
ITA
FCI
Credit-to-GDP Gap
Quarters
1980q1 1985q1 1990q1 1995q1 2000q1 2005q1 2010q1 2015q1
FCI
Credit-to-GDP Gap

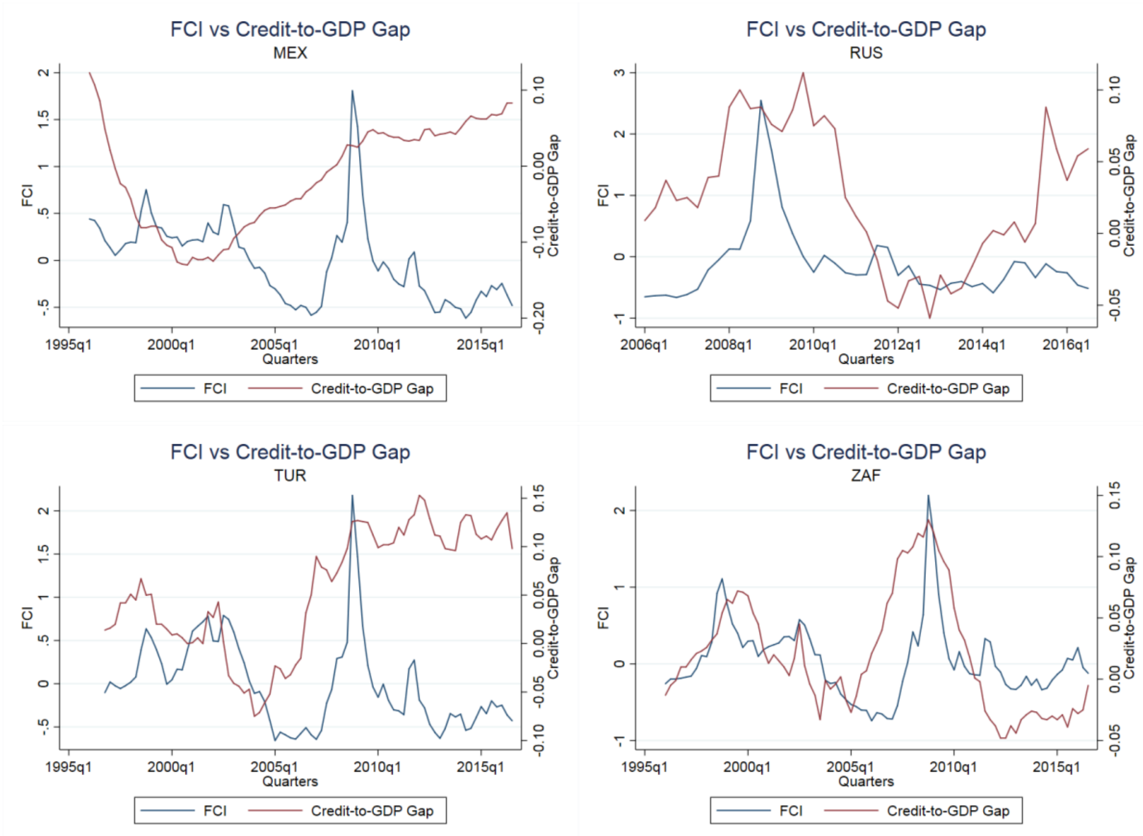

FCI vs Credit-to-GDP Gap
JPN
FCI
Credit-to-GDP Gap
Quarters
1975q1 1980q1 1985q1 1990q1 1995q1 2000q1 2005q1 2010q1 2015q1
FCI
Credit-to-GDP Gap


FCI vs Credit-to-GDP Gap
SWE
FCI
Credit-to-GDP Gap
Quarters
1980q1 1985q1 1990q1 1995q1 2000q1 2005q1 2010q1 2015q1
FCI
Credit-to-GDP Gap


FCI vs Credit-to-GDP Gap
USA
FCI
Credit-to-GDP Gap
Quarters
1975q1 1980q1 1985q1 1990q1 1995q1 2000q1 2005q1 2010q1 2015q1
FCI
Credit-to-GDP Gap

b. Emerging market economies




FCI vs Credit-to-GDP Gap
MEX
FCI
Credit-to-GDP Gap
1995q1
2000q1
2005q1
2010q1
2015q1
Quarters
FCI
Credit-to-GDP Gap
FCI vs Credit-to-GDP Gap
RUS
FCI
Credit-to-GDP Gap
2006q1
2008q1
2010q1
2012q1
2014q1
2016q1
Quarters
FCI
Credit-to-GDP Gap
FCI vs Credit-to-GDP Gap
TUR
FCI
Credit-to-GDP Gap
1995q1
2000q1
2005q1
2010q1
2015q1
Quarters
FCI
Credit-to-GDP Gap
FCI vs Credit-to-GDP Gap
ZAF
FCI
Credit-to-GDP Gap
1995q1
2000q1
2005q1
2010q1
2015q1
Quarters
FCI
Credit-to-GDP Gap