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The Term Structure of Growth-at-Risk

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Abstract

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

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I. Introduction

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

In this paper, we estimate the distribution of expected GDP growth for 11 advanced economies (AEs) using panel quantile regression methods.[1] Our objectives are to measure the median and the lower 5th percentile of the distribution of expected real GDP growth — which we call growth-at risk (GaR) — and then how they change over the projection horizon as a function of financial conditions. Concretely, GaR is the conditional growth at the (lower) 5th percentile of the GDP growth distribution, and thus captures expected growth at a low realization of the GDP growth distribution. For example, higher growth and lower volatility would lead to a higher GaR, and lower growth and higher volatility would lead to a lower GaR. By also estimating the term structure, we can evaluate whether higher GaR achieved in the near-term with loose financial conditions is long-lasting and sustainable.

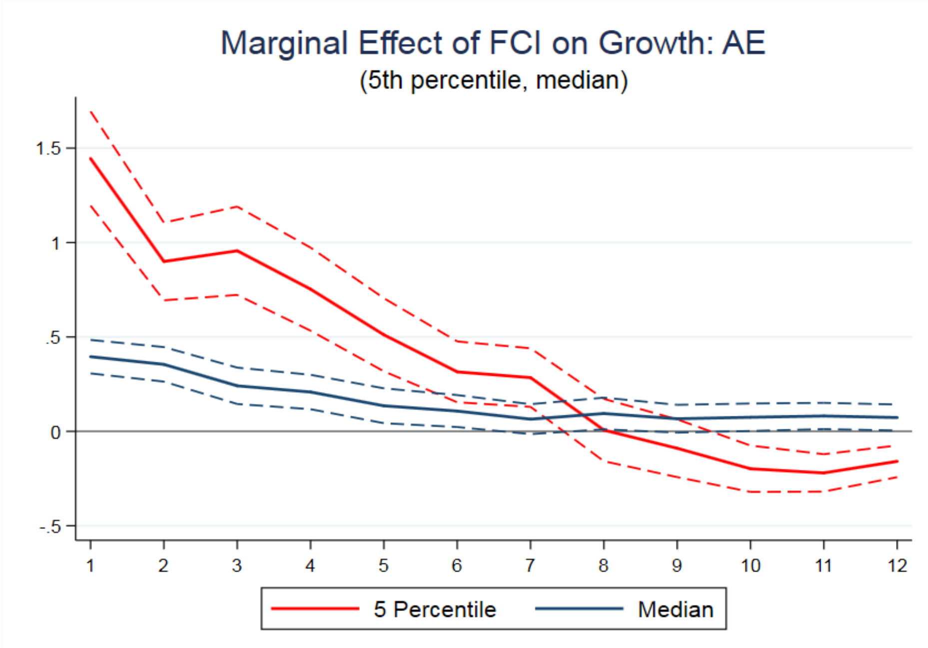
We model empirically the distribution of future real GDP growth as a function of financial conditions, economic conditions, inflation, and credit growth. This model builds on estimations for the US in Adrian, Boyarchenko, and Giannone (2018). We use local projections to estimate the dynamic response of GDP growth moments from one to twelve quarters, which allows us to explore the evolution of risk over the forecast horizon.

Figure 1 provides 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, coefficient estimates on the financial conditions index (FCI) from panel quantile regressions for the lower 5th percentile and the median of the distribution of GDP growth (average quarterly growth for the cumulative period ending in quarters 1 through 12, at an annual rate) are shown. Higher FCI represents looser financial conditions. The positive coefficients in near-term quarters for both the 5th percentile and median indicate that the marginal effects of looser financial conditions are to significantly boost expected growth and reduce downside risk. But the decline in coefficients over the projection horizon suggest the impetus from initial looser financial conditions will decline or subtract from average expected cumulative growth

[1] The 11 AEs include Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, Sweden, and the US, and are the complete set covered in Chapter 3 of the IMF Global Financial Stability Report Oct. 2017.

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



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.

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

We allow for nonlinear effects of FCIs on the growth distribution through financial vulnerabilities that could amplify a negative shock. In particular, we evaluate whether the effect of loose financial conditions would be amplified by rapid credit growth. High credit growth has been shown to help predict the duration and severity of a recession (Jorda, Schularick and Taylor, 2013), and the credit-to-GDP gap a predictor of recessions (Borio and Lowe, 2002). We define a credit boom build-up by a dummy variable when both FCI and credit growth are in the top 30 percent of their respective distributions. The estimated coefficients on the dummy suggest that a credit boom forecasts significantly lower GaR in the medium term than when just financial conditions are loose.

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

The estimations indicate meaningful differences in the GaR term structure depending on the initial level of financial conditions. A key result is that GaR conditional on high FCI and a credit boom is substantially higher in the near-term and lower in the medium-term; this is more pronounced relative to GaR conditional on average FCI. Specifically, when FCIs are in the top 10 percent, GaR falls substantially, from about 0.5 percent to -2.5 percent between the short- and medium-term horizons, while the GaR for initial average FCI (defined by the middle 40 percent) increases modestly over the horizon.

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

Our results are robust to important alternative specifications. 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 conditional distribution of future GDP growth. The similarity in empirical results is promising for forecasting since the two-step procedure may be easier to incorporate into regular macroeconomic forecasting exercises. The intertemporal GaR tradeoff is also robust to excluding the Global Financial Crisis in 2008 to 2009, though estimates of GaR are not as low once this episode of large negative growth is excluded and the tradeoff is less steep. Finally, results from applying this model to only the US are similar to results for all the AEs. We also show for the US that our results are robust to controlling for monetary policy independent of financial conditions.

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

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

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

Our paper is related to empirical studies of the effects of financial conditions on output. As mentioned, we build on Adrian et al (2018), who document that financial conditions can forecast downside risks to GDP growth. Other papers look at changes in risk premia and financial conditions on output. Sharp rises in excess bond premia can predict recessions, consistent with a model of intermediary capital constraints affecting its risk-bearing capacity and thus risk premia (Gilchrist and Zakrajsek, 2012). Also, financial frictions result in changes in borrowing being driven by changes in credit supply (see Lopez-Salido, Stein, and Zakrajsek (2017), Mian et al (2015) and Krishnamurthy and Muir (2016)). The 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 robustness results, and highlights that a two-step OLS regression method and the quantile estimations in this paper lead to very similar tradeoff results. Section 6 concludes.

2. Modeling growth-at-risk

We build on the Adrian et al (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 11 countries and allow for nonlinearities from financial vulnerabilities, approximated by high credit growth. The 11 countries are the AEs included in the IMF's GFSR in October 2017, and represent a set that have sufficient data for estimation.

a. Model estimation with quantile regressions

The estimates of the conditional predictive distribution for GDP growth are from panel quantile regressions. Quantile regressions allow for a general modeling of the functional form of the conditional

GDP distribution. We denote $\Delta y_{i,t+h}$ as the annualized average growth rate of GDP for country *i* between *t* and *t+h*, and $x_{i,t}$ a vector of conditioning variables. The conditioning variables include FCI, GDP growth, inflation, a dummy variable for credit boom, defined by the interaction of high FCI and high credit growth, and a constant.

In a panel quantile regression of $\Delta y_{i,t+h}$ on $x_{i,t}$ the regression slope $\delta_{\alpha}^{(h)}$ is chosen to minimize the quantile weighted absolute value of errors

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

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

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

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

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

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

We measure growth by cumulative growth between *t* and *t+h* at an annual average rate to make it easier to interpret the units, rather than cumulative growth rates sometimes used in other applications of the local projection method.[2] 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

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

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,[3] 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 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).[4] Inferential procedures based on bootstrap resampling with 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. To account for temporal dependence present in the data, we use a block-bootstrap (Lahiri, 2003, and Kapetanios, 2008). This consists of resampling ‘blocks’ formed of contiguous rows of data.[5] In the analysis below, we generate bootstrap standard errors considering block widths of 4, 6 and 10 quarters, but report only block widths of 4 quarters as results are quite similar. All standard errors estimates are based on 10,000 bootstrap samples.

Below we generally report the direct estimates from the quantile regressions for the 5th, 50th, and 95th percentiles, rather than estimates from a smoothed distribution. However, we also show probability density functions which we recover by mapping the quantile regression estimates into a skewed t-distribution, following Adrian et al (2018), which allows for four time-varying moments – conditional

[3] See Jorda (2005) and Stock and Watson (2018).
[4] The literature to date on estimating panel quantile regressions with fixed effects has focused mostly on the problem where the number of cross-sectional units N far exceeds T (Koenker, 2004). In general, estimation and associated asymptotic properties are based on restricting fixed-effects to be invariant across different quantiles (Canay, 2011).
[5] This assumption that errors are uncorrelated across countries is not unusual. It would be difficult to change in our estimations because country-level data do not have uniform availability, and we have unbalanced panels.

mean, volatility, skewness, and kurtosis. To do so, we fit the skewed *t*-distribution developed by Azzalini and Capitaion (2003) in order to smooth the quantile function:

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

where $dT(\cdot)$ and $T(\cdot)$ respectively denote the PDF and CDF of the skewed *t*-distribution. The four parameters of the distribution pin down the location μ, scale σ, fatness ν, and shape θ. We use the skewed *t*-distribution as it is a flexible yet parametric specification that captures the first four moments.

b. Conditions for a credit boom

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

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

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

We use growth in the private nonfinancial credit-to-GDP ratio measured over the previous eight quarters.[6] We define $\lambda_{i,t}$ when both FCI and growth are in the top three deciles of their distributions respectively. The joint condition helps to exclude periods when credit growth is high because it has just started to reverse from a bust and when FCIs are still near recession tightness, since those conditions would not be consistent with a credit boom.[7]

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. To fix ideas, changes in the distribution of GDP growth are generated by changes in the price of risk, which is measured via financial conditions. Loose financial conditions can lead to a buildup of vulnerabilities in the presence of financial frictions, such as capital requirements or VaR models of financial institutions. When asset prices rise, increased net worth can make regulatory constraints for financial intermediaries less binding, leading to a reduction in risk premia (He and Krishnamurthy, 2013) and additional risk-taking (Adrian and Shin, 2014). In addition, lower risk premia may be associated with exuberant sentiment, and suggest that periods of compressed risk premia can be expected to be followed by a reversal of valuations (Greenwood and Hanson, 2013). Lopez-Salido, Stein, and Zakrajsek (2017) show that periods of narrow risk spreads for corporate bonds and high issuance of lower-rated bonds are useful predictors of negative investor returns in the subsequent two years. The negative returns lead to lower growth, likely from a pullback in credit supply, providing empirical evidence of an intertemporal

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

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

tradeoff of current loose financial conditions at some future cost to output. Loose financial conditions may also ease constraints for borrowers, who then can accumulate excess credit because they do not consider negative externalities for aggregate demand (see, for example, Korinek and Simsek, 2016).

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

We estimate the model for the 11 AEs that were included in the IMF Oct. 2017 GFSR Chapter 3. Quarterly data for real GDP growth and consumer price indexes (CPI) to measure inflation (year-to-year percent change) for the 11 countries are available from the International Financial Statistics (IFS).[8] Nonfinancial credit-to-GDP ratios are from the BIS, and credit is to households and businesses.

We construct FCIs for each of the 11 countries using up to 17 country-level price-based variables.[9] The FCI captures domestic and global financial price factors, such as corporate credit risk spreads, equity prices, volatility, and foreign exchange. The starting dates vary for each of the variables, and the starting dates for each of the data series and the start date for the model estimation by country is shown in Appendix A.

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,

[8] Estimates of potential growth for the 11 countries are not available on a consistent basis, or for the full sample periods.

[9] The variables include interbank spreads, corporate spreads, sovereign spreads, term spreads, equity returns, equity return volatilities, equity implied volatilities, changes in real long-term rates, interest rate implied volatilities, house price returns, the percent changes in the equity market capitalizations of the financial sectors to total market capitalizations, equity trading volumes, expected default frequencies for banks, market capitalizations for equities, market capitalizations for bonds, domestic commodity price inflation rates, and foreign exchange movements. These data are the same as used to construct the FCIs that were used in the October 2017 GFSR. However, we do not use the same FCIs.

and Reichlin (2011).[10] This approach has three benefits: (i) it controls for financial conditions of (current) macroeconomic conditions without complicating its forecasting properties for GaR, (ii) it allows for dynamic interaction between the FCIs and macroeconomic conditions, which can evolve over time, and (iii) it allows for a flexible estimation procedure that can deal with some financial indicators being available in different time periods.

The model takes the following form:

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

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

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

Summary statistics for the panel of AEs are presented in Table 1. Values in the tables are averages across countries and across time. The values represent the sample estimation periods starting in 1975, 1980, or 1981 for most of the AEs, except for Spain which starts in 1992 (see Appendix A). The roughly forty-year sample period for most of the AEs allows us to capture multiple business and credit cycles, rather than only the global financial crisis.

For our sample period, average annual real growth is 2.2 percent and inflation is 3.5 percent. The average credit-to-GDP ratio is 1.34, growth in the ratio is 0.55 percent, indicating credit grew faster than GDP on average through the sample period. Periods when the credit boom λ is equal to 1, when credit growth and FCI are each in the top three deciles of their distributions, represent 7.7 percent of sample. We then can observe how a configuration of high FCIs with positive credit growth will evolve and determine growth over horizons up to three years later.

Regression estimates (not shown) show that FCIs 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.

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

Charts of FCI and credit-to-GDP growth for the 11 countries are in Appendix B. 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 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 are loose than when they are moderate; this comparison provides an estimate of the intertemporal risk tradeoff relative to typical conditions. Finally, we show the term structures of both median growth and GaR by initial FCI groups, to illustrate a potential intertemporal risk-return tradeoff from initial loose financial conditions. The estimates show that while initial loose FCI and high credit project higher expected growth and GaR in the near-term, the growth differential declines modestly while the GaR decline is substantial, suggesting sharp increases in downside risks without the benefit of higher growth.

a. Estimated FCI coefficients with interaction

Figure 1 shown above presents 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.

Figure 2 shows the coefficients on λ for the 5th percentile quantile regressions over the projection horizons. The coefficients on λ 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. 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.

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

b. Time series of average GaR

Figures 3 shows the time series of average GaR estimates (averaged across countries), at the projection horizon of four quarters (h = 4). Also plotted for h = 4 are the conditional median and the 95th percentile, as well as realized growth (shifted forward by four quarters). The time series reveals that lower projected median growth is associated with lower GaR, consistent with conditional growth and volatility being negatively correlated. In sharp contrast, there is very little variability at the 95th percentile, suggesting greater variability for downside risk than upside risk.

In particular, the mean GaR for AEs over the sample period is -1.4 percent, with a standard deviation of 1.4, whereas the standard deviation of the 95th percentile is lower at 0.28, even though the mean 95th percentile is much higher, at 5.2 percent. Basically, the conditional 95th percentile shows little variation, while GaR is highly variable. The downside risk as represented by GaR shows much greater variability than upside risk as the conditional mean changes over time.

These results expand on Adrian et al (2018) by demonstrating the results for a panel of 11 AEs, and expanding the forecast horizon to twelve quarters, using local projections. For comparison, we present below the time series results for the US only (see section 5b, figure 12).

c. Probability density functions of expected growth and GaR

In this section, we show the entire probability density function derived by fitting the quantile regression estimates to a skewed-*t* distribution, as described above by equation (4). The growth distributions can be used to illustrate the conditional expected GaR as well as the tails, and the dynamics of the term structure.

The expected growth distribution conditional on high FCI (top 1 percent) and credit boom for $h = 4$ is fairly tight and has very little mass in the left tail (figure 4a). In contrast, the distribution at $h = 10$ for the same initial high FCI and credit boom is wider and has a lot of its mass in the left tail. These distributions indicate substantial shifts and increased downside risks from h=4 to h=10 when initial financial conditions are loose in a credit boom. For high FCI but without a credit boom, the distribution also shifts between h=4 and h= 10, but it is much less pronounced, suggesting GaR has fallen only moderately (figure 4b).[11]

d. Term structures of GaR by initial FCI groups

The probability density functions shown in figure 4 provide the entire smoothed distribution for a given FCI, credit boom indicator, and projection horizon. Next we look more closely at risks in the lower tail, specifically the 5th percentile, although the density functions indicate that results would be robust to other percentiles in the near vicinity, such as the 2.5, 7.5, or 10th percentiles. For the 5th percentile, we can show the term structure of GaR based on different initial FCI decile groups to evaluate if loose FCI is more likely to have both lower risk in the near-term and higher risk later. We show GaR term structure estimates based on initial average FCI values for four groups: in the top 1 percent (very loose financial conditions), top decile (loose financial conditions), bottom decile (very tight financial conditions), and middle 40 percent, and by whether λ, credit boom, is equal to zero or one.

The term structures indicate an intertemporal tradeoff for downside risk when initial FCIs are loose. When initial FCIs are in the top decile or higher, the estimated GaRs are initially high but then fall over most of the projection horizon, indicating downside risks increase in the medium-term; the downward slope is much sharper when there is also a credit boom (figure 5a and 5b). Specifically GaR is about 1 percent in the near-term for very loose FCIs (Top 1) and credit boom, but it then falls significantly over the projection horizon to less than -2.0 percent at around h=8, a swing of more than 3 percentage points; the decline in GaR for FCI in the top decile (Top 10) is about 2.5 percent. We use the four middle deciles (labeled Mid 40) of initial FCI values to represent "typical" moderate conditions, to approximate for expected growth and downside risk when FCIs are neither high nor low. Estimated GaRs for initial FCI in the mid-range (Mid 40) rise initially and then level out at about -0.5 percent in the medium-term. That is,

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[11] We can also express the changes in distributions over the projection horizon into the probability of GaR falling below zero (not shown). The probability in the near-term is negligible, but rises significantly to almost 20 percent in the medium-term for high FCI and a credit boom. Without a credit boom, the probability of negative growth rises more modestly from zero to about 9 percent for high FCI.

the term structure for the moderate FCI group slopes upward rather than downward, as moderate FCIs do not increase downside risks to growth in the medium-term.[12]

To compare the differences in the GaR term structures, we calculate the differences between the Top 1 percent and the Mid 40 FCI groups, and we test for the statistical difference between the term structures by calculating standard errors by bootstrapping the differences in GaRs at each horizon h. The differences in the term structures between the average FCI in the Top 1 with a credit boom and Mid 40 are positive and statistically significant in the near-term, and turn negative and statistically significant in the medium-term (figure 6a), indicating that the lower downside risks in the near-term from the loose FCI reverse and become larger in quarters further out. The difference in term structures for Top 1 and Mid 40 for no credit boom is also positive and significant in the short-term, and falls over the projection horizon, but the magnitude of the decline is smaller (figure 6b). Under credit boom conditions, the difference in GaR is about 2 percentage points lower at around $h = 8$ to 10 than when no credit boom, suggesting credit growth plays an important role in amplifying changes in financial conditions, consistent with theories of macrofinancial linkages.

Returning to the term structures in figure 5, 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 the lowest decile is very low in the short-run (less than -6 percent), suggesting the economy is in a deep recession or a financial crisis. However, these effects dissipate over time and for the AEs converge in the medium term to the same GaR as for initial moderate financial conditions. We view very low FCIs as reflecting the realization of a negative shock, which lead to a sharp tightening of FCIS, 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 loose FCIs that also lead to greater financial vulnerabilities set the stage for sharper tightenings in FCIs when there is a negative shock (Brunnermeier and Pedersen (2009), Brunnermeier and Sannikov (2014), and Adrian and Shin (2014)). Or sharp tightenings in FCI may reflect sharp sentiment reversals that are triggers that interact with vulnerabilities and lead to recessions and credit busts (Minsky 1977). We leave to future work an approach to estimating the term structures of the joint distribution between FCIs and GDP growth.

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

[12] Note that because credit boom was defined by high credit growth and FCI in the top three deciles, the estimated term structures of GaR for the Mid40 do not differ for credit boom and not credit boom.

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

To see this tradeoff, we plot the projected median and GaR term structures for the Top 10 and Mid 40 FCI groups, for high credit and low credit (figure 7). First, median growth is higher in the near-term for FCI in the Top 10 than for Mid 40 in both cases, and the gap shrinks over time, mostly as the projected median growth for Top 10 FCI falls. That is, the marginal contribution to growth from high FCI diminishes somewhat over the projection horizon. Second, GaR is higher (downside risk is lower) for top decile FCI than for Mid 40 FCI in the near-term, but it then falls over the projection horizon. The reversal is substantial for credit boom conditions. Note also that the projected median growth for typical Mid 40 FCI is flat over the projection horizon, at slightly under 2 percent, 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 8 plots the information in Figure 7 as differences in the term structures between the top decile and the neutral case for the projected medians and GaR. The differences make it more evident that the decline in GaR is much steeper than the decline in the median growth in all four cases. This configuration illustrates the costs of a credit boom. In contrast, when there is not a credit boom, the decline in GaR – the amplification effect – is less sharp, and the decline in the marginal boost to growth is very modest. This configuration illustrates a situation of slower growth but also lower downside risks from loose financial conditions.

f. Interpreting the intertemporal risk-return tradeoff

We have shown with GaR and the probability density functions that the differences in term structures between high and moderate initial FCI groups are statistically different. While we do not model the determination of FCIs, and our estimates are not treatment effects, the increased downside risks in the medium-term associated with looser financial conditions (lower price of risk) suggests that policymakers might want to incorporate tradeoffs when evaluating future downside risks.

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

But a more economically significant tradeoff might exist if the welfare function were to incorporate that the costs of large downside risks are high. For example, recessions can lead to permanent losses in output, rather than a temporary decline with a rebound back to trend, and recessions with banking crises have greater losses (Cerra and Saxena, 2008). 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). Costs may also increase with the severity of the recession, which often are greater when there is also a banking crisis or other financial crisis. Reinhart and Rogoff (2009) and Schularick and Taylor (2012) document that recessions with financial stress are much more costly and may take five to eight years to return to pre-crisis levels, several years longer than recoveries following normal recessions. Wolfers (2003) finds that greater macroeconomic volatility and higher unemployment has an adverse impact on different social welfare metrics.

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

5. Robustness

We provide a number of robustness checks to our estimations, starting with an alternative two-step OLS estimation of mean and variance rather than quantile estimates, and find very similar results. We then report some results excluding the Global Financial Crisis peak years of 2008 to 2009, and find that the intertemporal risk tradeoffs remain, although GaR estimates are not as low as when we include the more extreme negative outcomes. We also report results specifically for the US, and show results are similar to Adrian et al (2018) and robust to a slightly different empirical model and different FCIs. The US results also are robust to adding monetary policy, suggesting that the effects of financial conditions on GaR are not simply reflecting monetary policy.

a. Growth at risk in a heteroskedastic variance model – Two-step OLS regressions

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

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

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

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

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

We first estimate the relationship between the change in output on financial conditions and the other variables, including country fixed effects, equation (8). We then use the residuals from the estimated equation and regress $\ln \hat{\varepsilon}_{i,t+h}^2$ onto the right-hand side variables of equation (9).[13] 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.[14] 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)

[13] Note that the estimated residuals $\hat{\varepsilon}_{i,t}$ are not a "generated regressor" and thus they can be used directly in the second stage equation (see Pagan, 1984).
[14] Given the assumption of a conditional Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth.

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:[15]

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

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

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

We derive the GaR term structures and condition on initial FCIs and credit boom, based on the two-step OLS estimates. Figure 10 is the counterpart to Figure 5, which was 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

[15] 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.

procedure are consistent with the existence of a substantial intertemporal tradeoff found with the quantile regressions.

b. Quantile estimates excluding the Global Financial Crisis

The sharp declines in GDP growth for many AE countries, along with the steep tightening of FCIs in 2008 when credit-to-GDP had been rising, raises the possibility that this episode is driving the reported GaR results. We test this possibility by dropping from the sample the years 2008 to 2009 (we effectively replace growth in those years with average growth in 2007 and 2010). The results indicate the estimates of GaR at h=4 tend to be less negative from the baseline results, which is not surprising if we remove this episode with a sharp decline in GDP growth (figure 11). But, importantly the projected conditional distribution shows much greater downside variation than upside variation. In addition, the corresponding GaR term structures for initial Top 1 and Top 10 FCI continue to slope downward, though the slope is less steep (figure 11 b and c). We interpret these results as indicating that the estimated GaR reflect a general relationship between financial conditions and the distribution of expected growth over many decades, since the mid-1970s, but the results are strengthened when the GFC is included in the estimation.

c. 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 quantile estimations based on just the US data (figure 12). The estimates for the US clearly illustrate the intertemporal risk tradeoff. While the estimated GaR is higher for the US than for AEs on average, the term structures for Top 1 and Top 10 show that the decline in GaR is similarly sizable, about 3 percent. In addition, the estimations for the US are very similar to Adrian et al 2018, and demonstrate the results are robust to different FCIs and modest changes in the empirical model. The model in this paper differs because we add inflation and a credit boom dummy variable.

d. Adding monetary policy to the US model

We also test for the possibility that the observed effects of FCI on GaR reflect monetary policy rather than the price of risk of risky assets. Brunnermeier et al (2017) emphasize that monetary policy has effects on GDP growth, and also on financial spread variables and credit, and it is important to separate the effects of financial variables on GDP growth from the effects of monetary policy. They focus on GDP growth but not the full distribution. To incorporate monetary policy, we first re-estimate the FCI for the US to control for current monetary policy, in the same way the FCI controls for macroeconomic conditions, as shown in equations (6) and (7). The re-estimated FCI is similar to the original FCI, and results based on the re-estimated FCI are very similar to results reported above. We then add residuals from a Taylor rule specification (federal funds rate minus the estimated Taylor rule rate) to the quantile regressions for the US, also using the re-estimated FCI. We show the results from a Taylor rule using the original specification (from St. Louis FRED).[16] The GaR term structure from the model with Taylor rule residuals is very similar to the estimates without, indicating the effects of FCI do not suffer from an omitted variable bias (figure 13).

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. The relationships we examine are rooted in macrofinancial linkages arising from financial frictions, such as asymmetric information and regulatory constraints, where a 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 5^{th} percentile of expected growth for horizons out to twelve quarters, which providres 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 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

[16] https://fredblog.stlouisfed.org/2014/04/the-taylor-rule/. The results are basically unchanged when using an alternative Taylor rule which includes an interest rate smoothing parameter https://www.frbatlanta.org/cqer/research/taylor-rule.aspx?panel=1

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. Moreover, the additional boost to expected growth from initial loose financial conditions and high credit diminishes over the projection horizon, suggesting that expected growth has not increased to offset the costs of greater downside risks.

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

The GaR measure that we develop offers promise as a way to translate financial stability risks to macroeconomic performance. While progress has been made to add macrofinancial linkages, a dominant paradigm has not yet emerged about how to incorporate them into expanded models that would be used regularly by policymakers. This empirical model takes a step forward to integration. The GaR measure ultimately could help in developing macroprudential policies. 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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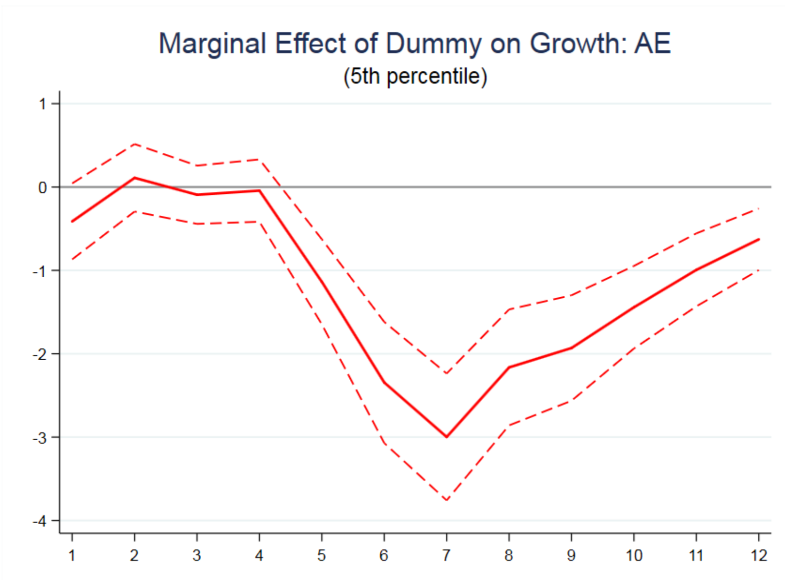
Table 1. Independent variables

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

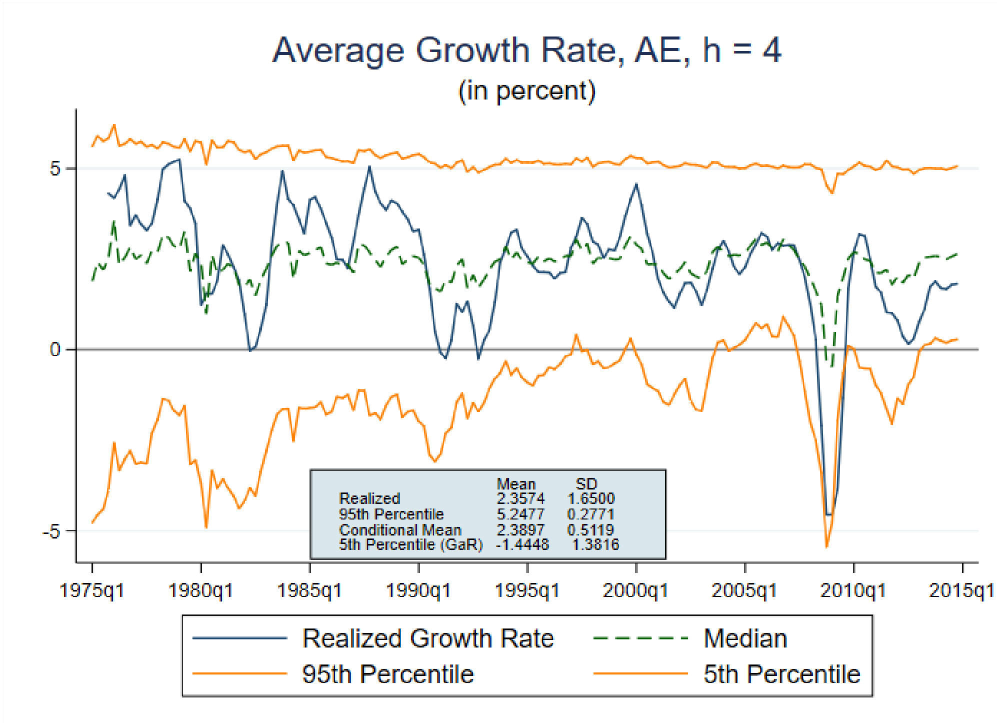
Note. Table includes descriptive statistics for 11 AEs: Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, Sweden, and the US. The start of the estimation period is either 1975 or 1980 for most of the advanced economies. Specific starting dates for each country are shown in Appendix A.

Figure 2. Coefficient estimates on credit boom for 5th percentile



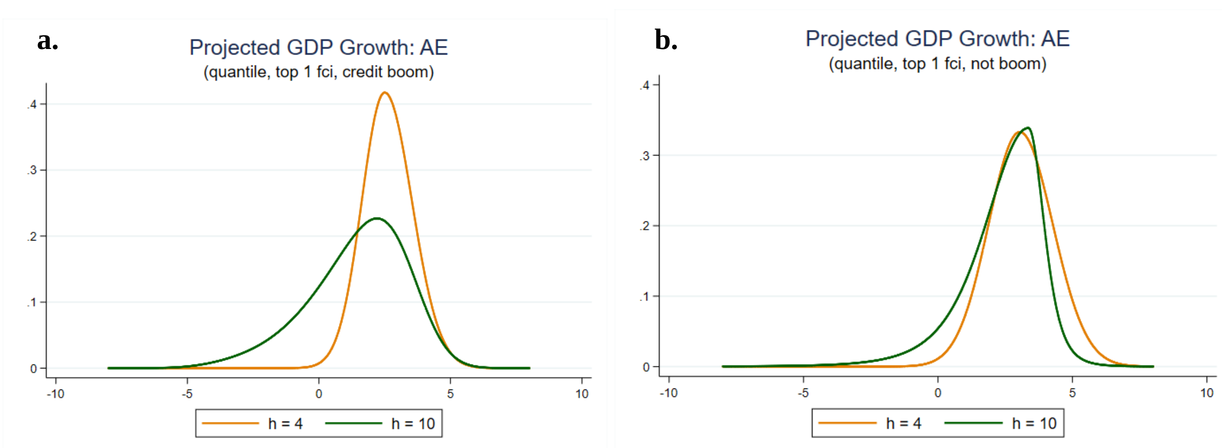
Note: Figures 2 plot the estimated coefficients on the credit boom dummy variable from panel quantile regressions for the 5th percentile, from one to 12 quarters into the future. Estimates are based on local projection estimation methods, and standard errors are estimated using bootstrapping techniques.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

Figure 3. Average growth-at-risk, median, and 95th percentile at *h* = 4



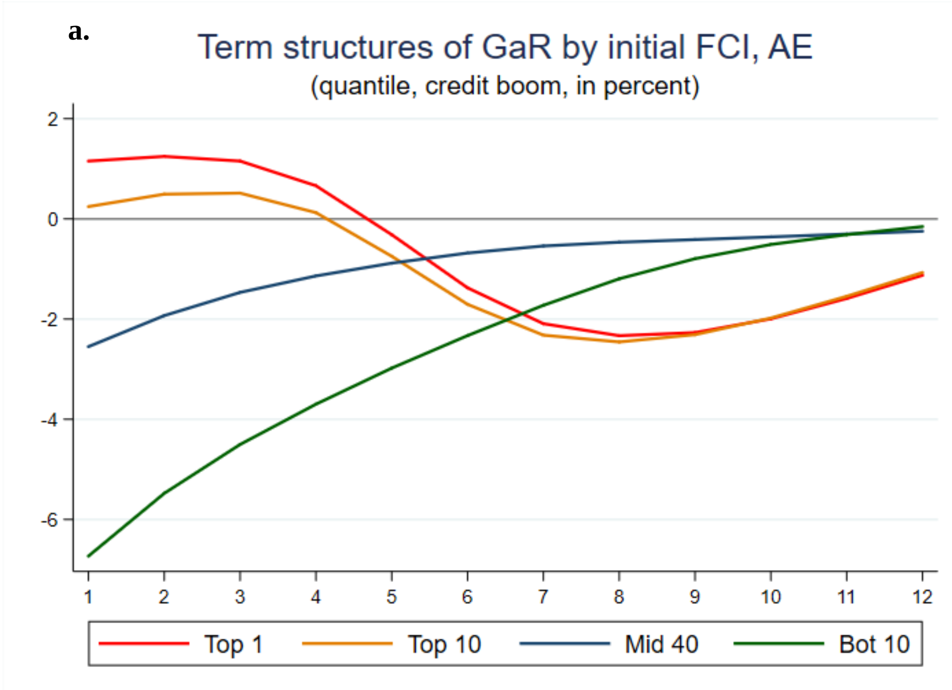
Note. Figures plot the cross-country averages of conditional mean growth, growth at risk (5th percentile), and 95th percentile, derived via estimation of the distribution of growth from quantile regressions. Advanced economies include 11 countries with data for most from 1973 to 2017.

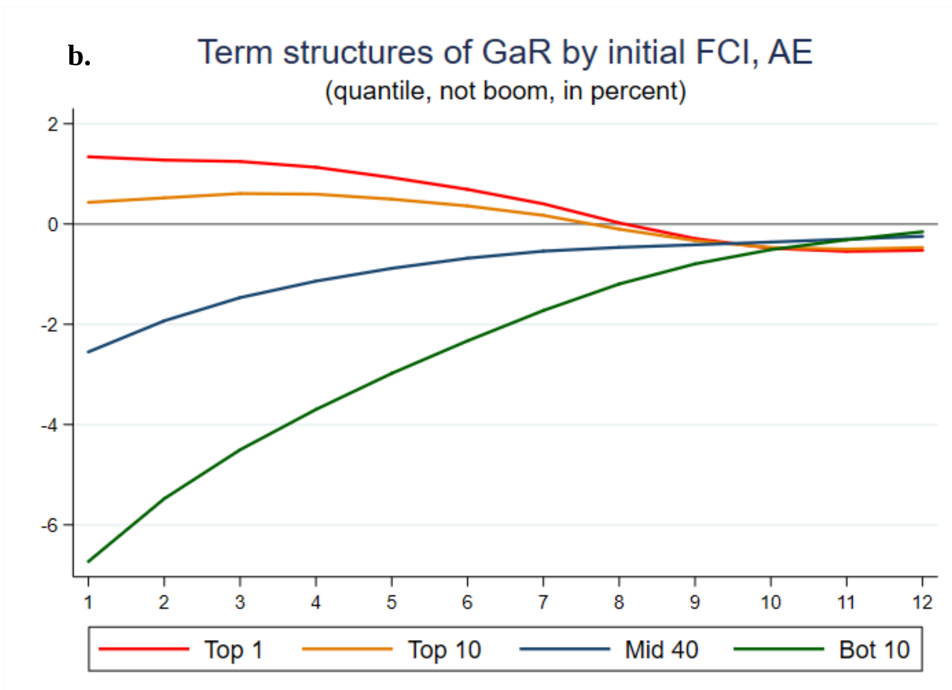
Figure 4. Probability density functions of conditional GDP growth



Note. Probability density functions are estimated using panel quantile regression methods and fitted to a skewed t distribution. Advanced economies include 11 countries most with data from 1973 to 2017.

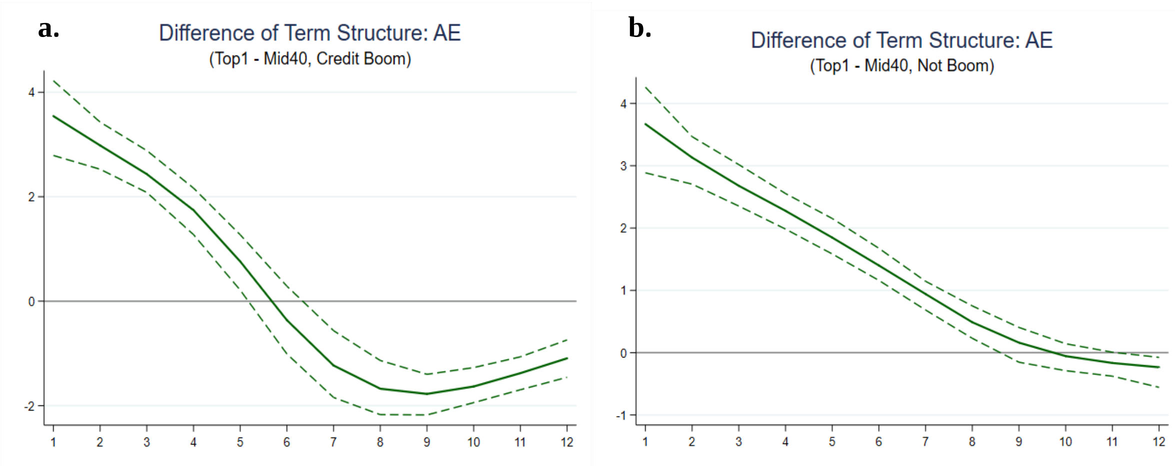
Figure 5. Term structures of GaR by initial FCI groups and differences





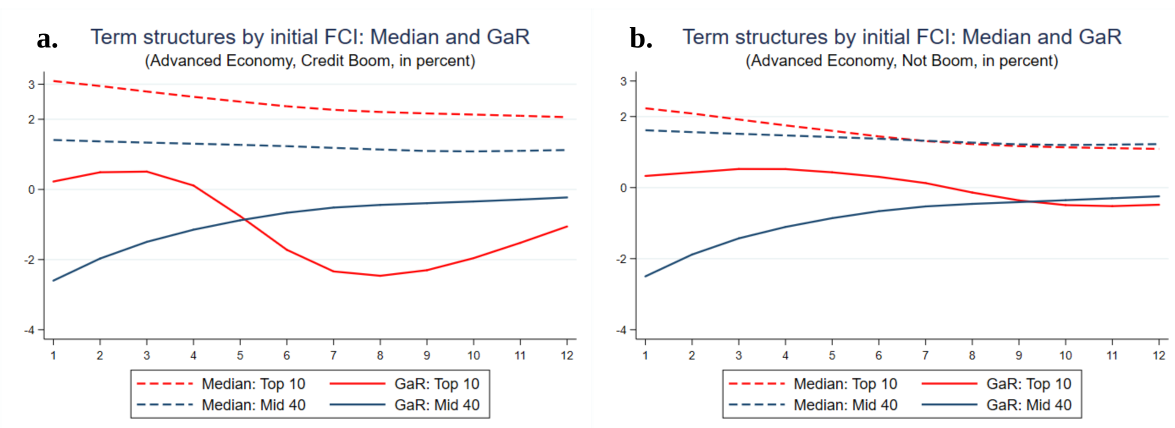
Note. Figures plot the GaR (expected growth at the 5th percentile) at an annual rate. The GaR projections are grouped on initial FCI levels by the top 1 percent, top decile, bottom decile, and a middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on 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 6. Differences of GaR term structures by initial FCI groups



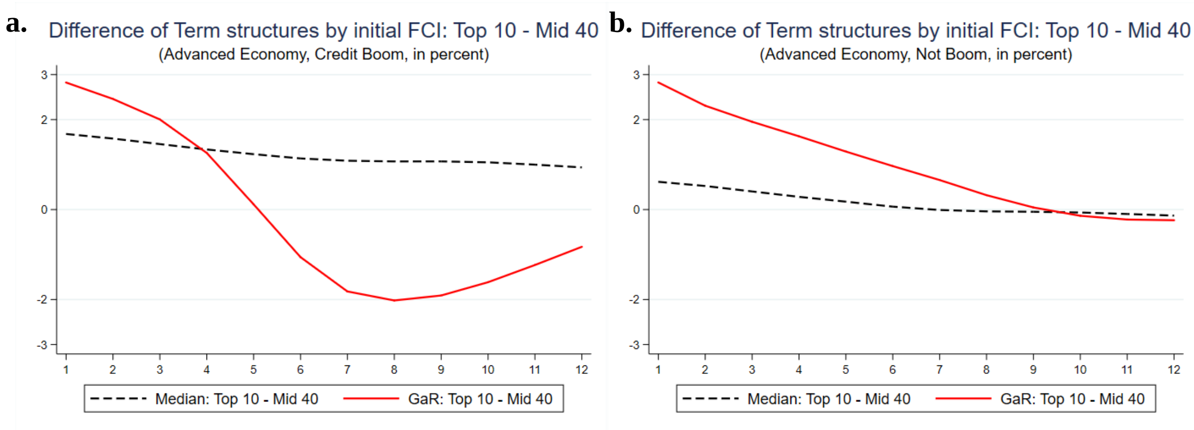
Note. Figures plot the differences in the GaR term structures of the top 1 percent (Top 1) minus the middle range (Mid 40). Standard errors are from bootstrapping techniques on the differences. Advanced economies include 11 countries with data for most from 1973 to 2017.

Figure 7. Term structures by initial FCI groups: Conditional Median and GaR



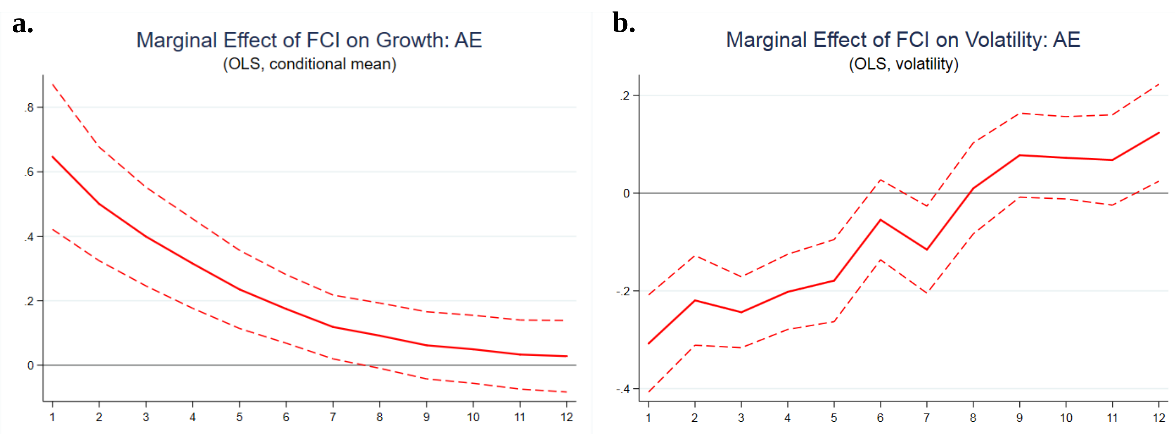
Note: Figures plot expected median and GaR (expected growth at the 5th percentile) at an annual rate for initial FCI levels top decile (Top 10) and middle range (Mid 40). Higher values of FCI represent looser financial conditions. Estimates are based on quantile regressions with local projection estimation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

Figure 8. Difference of term structures by initial FCI groups: Top 10 minus mid 40



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.

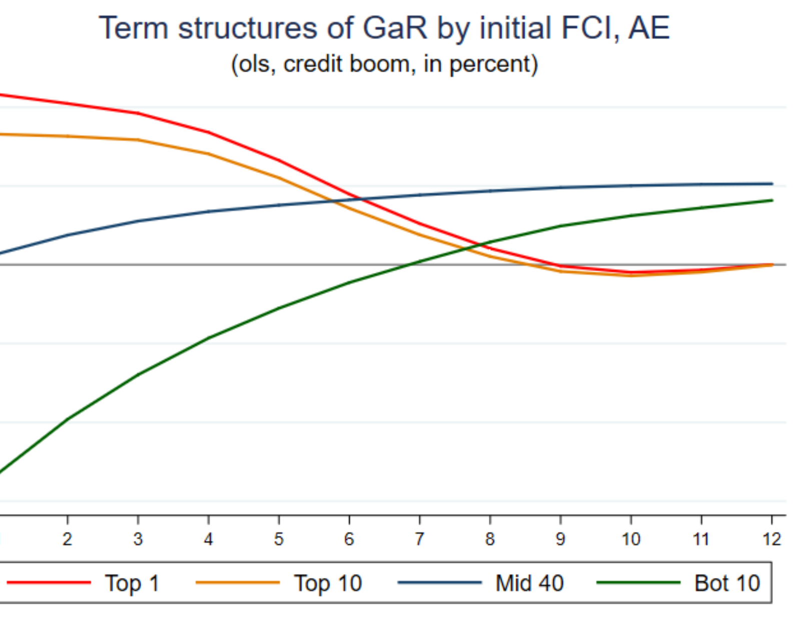
Figure 9. Marginal effects of FCI on growth and volatility from two-step OLS estimations



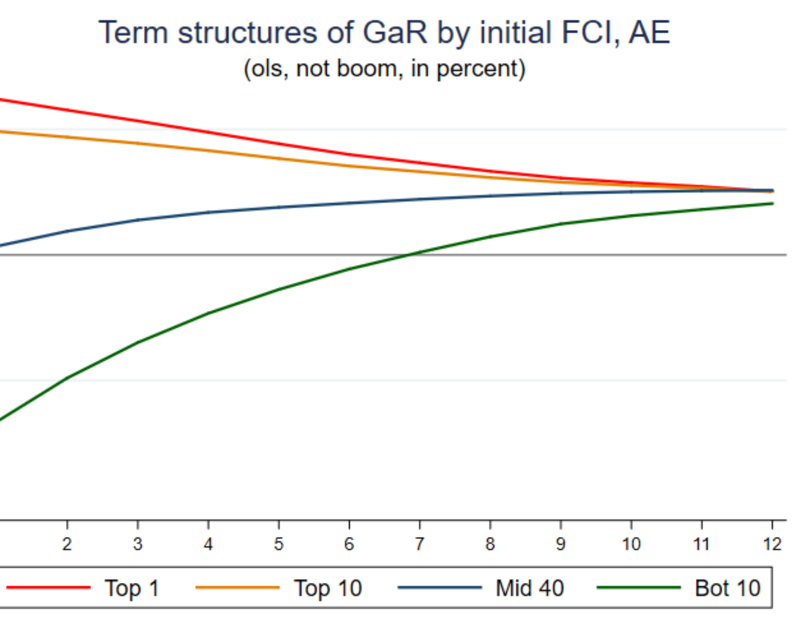
Note. Figures plot the estimated coefficients on the financial conditions index (FCI) and its interaction with high credit growth on GDP growth and GDP volatility for projection horizons from one to twelve quarters. Higher FCI represents looser financial conditions. Estimates are based on two-step OLS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

Figure 10. Term structures of GaR by initial FCI groups, from two-step OLS estimation

a.

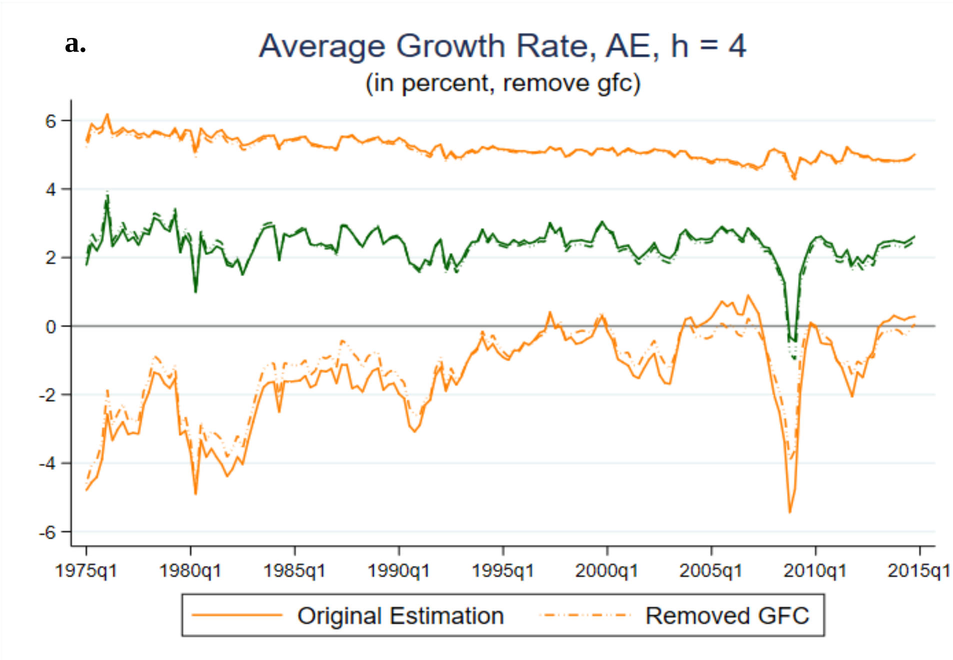


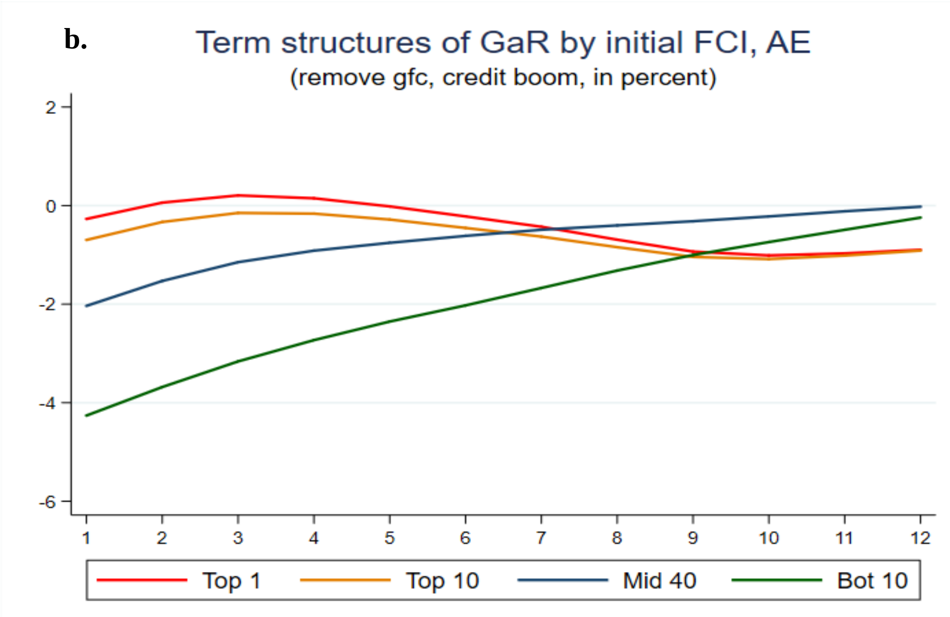
b.



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.

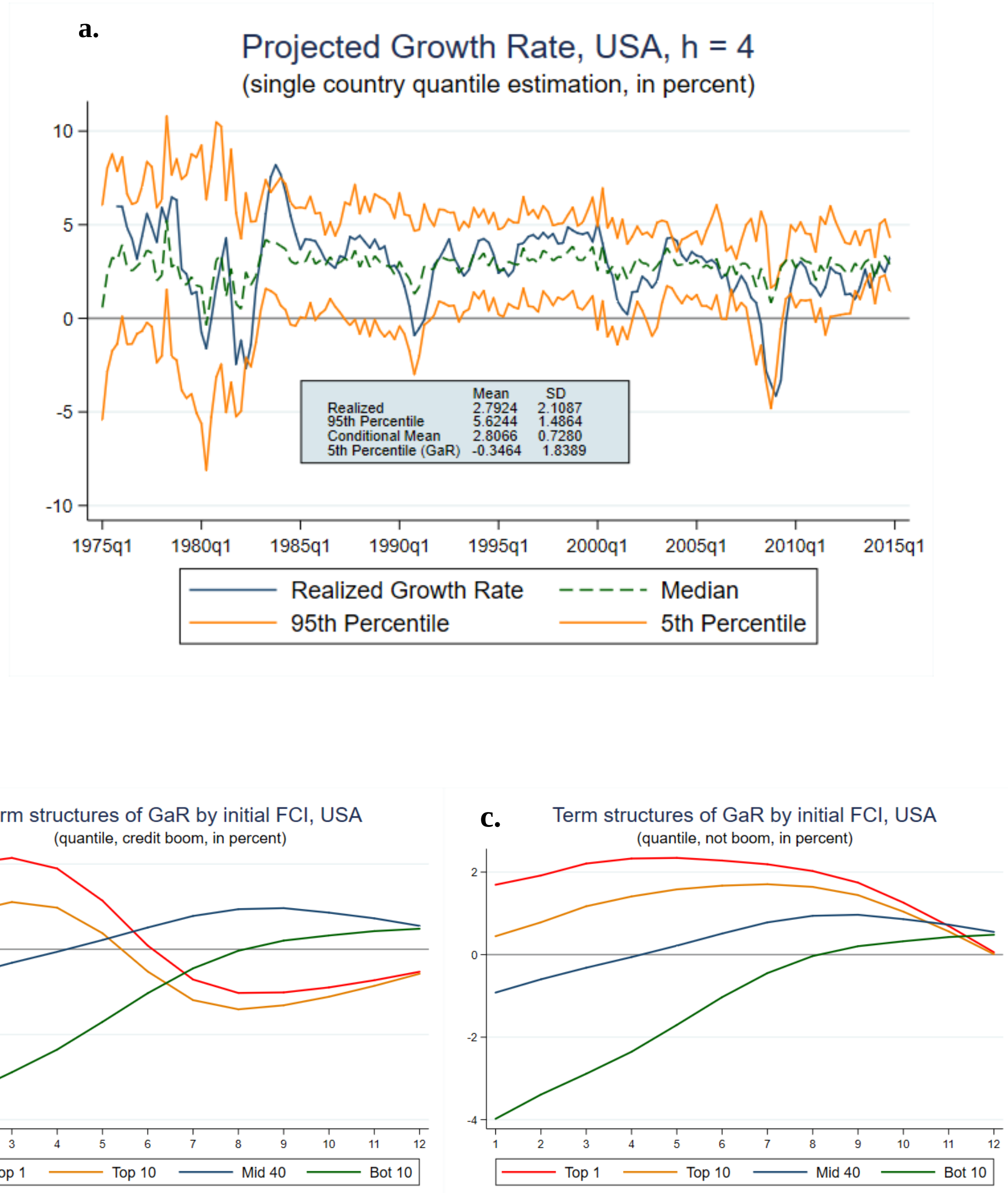
Figure 11. Estimates after excluding the global financial crisis





Note. Figures plot the time series of the expeted growth distribution from quantile regressions, excluding the financial crisis years 2008 and 2009. 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.

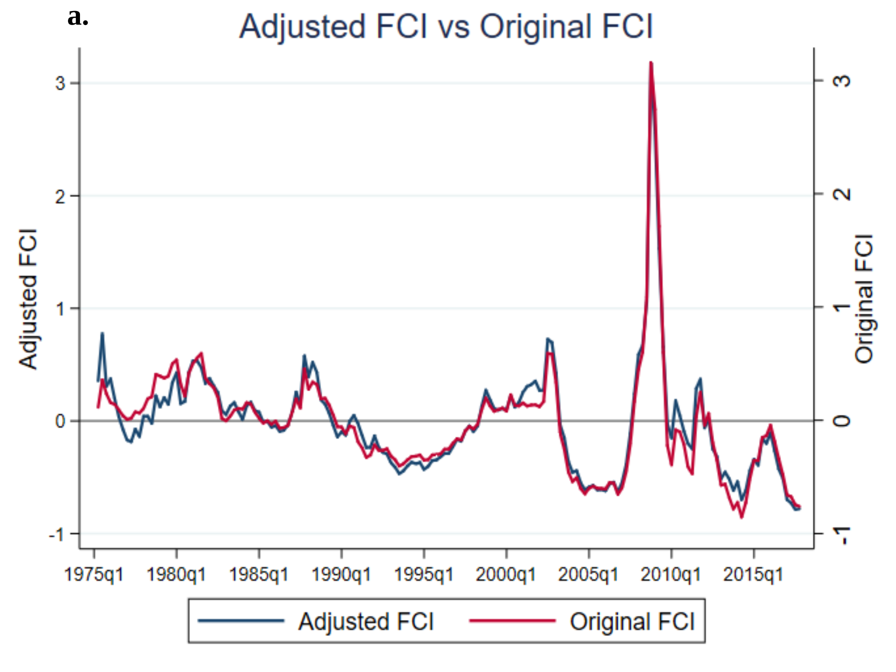
Figure 12. Projected growth-at-risk, median, and 95th percentile, USA, at h = 4



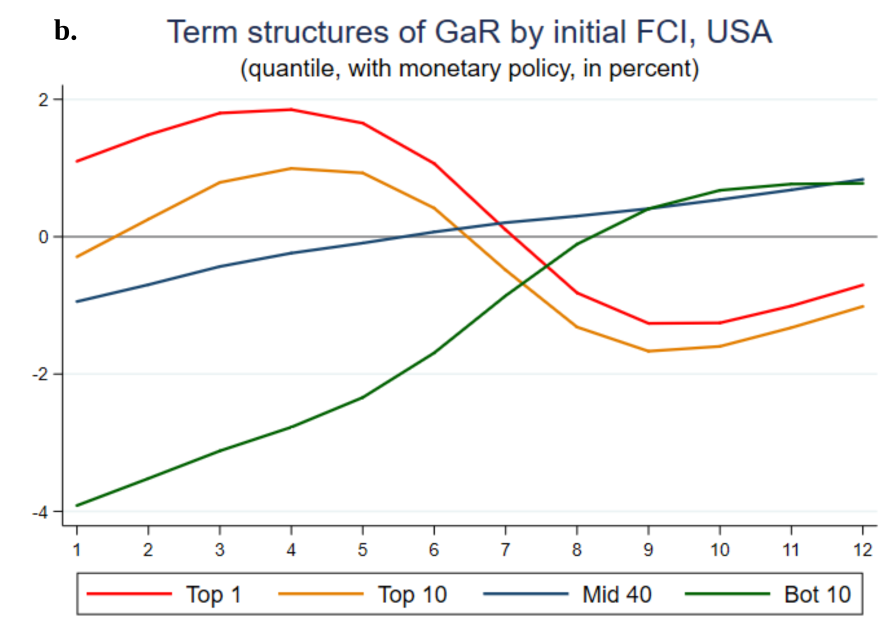
Note. Figures plot the time series of the expeted growth distribution from quantile regressions for the US only. GaR (expected growth at the 5th percentile) at an annual rate. The GaR projections are grouped on initial FCI levels by the top 1 percent, top decile, bottom decile, and a middle range (Mid 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.

Figure 13. Term structures of GaR with monetary policy, USA

a.



b.



Note. Figures plot the adjusted FCI estimated to also control for monetary policy, following the model in equations (6) and (7). Quantile regressions are estimated with Taylor rule residuals in addition to the adjusted FCI. 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.

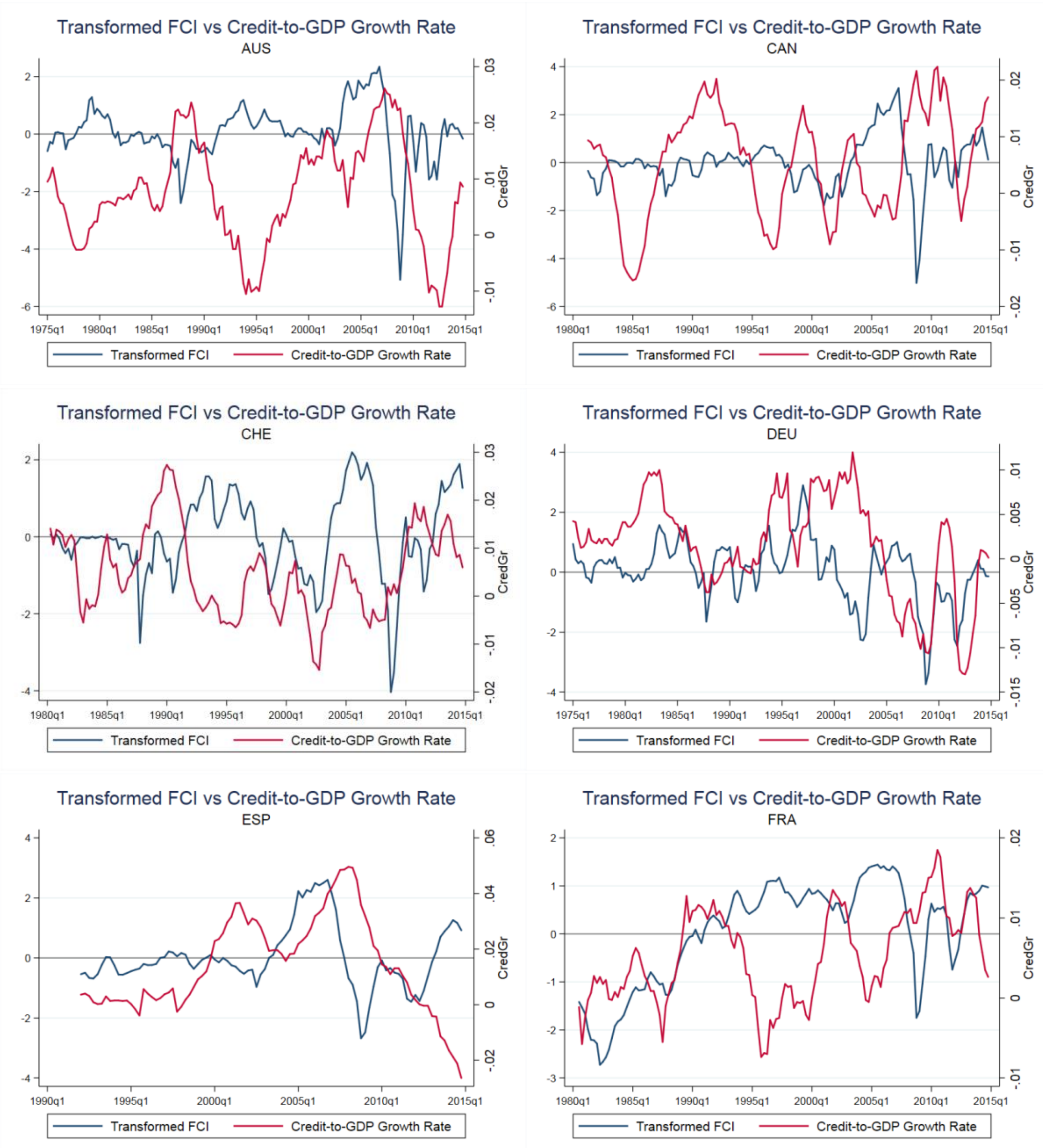
Appendix A. Start dates for model estimation and for individual components of FCI

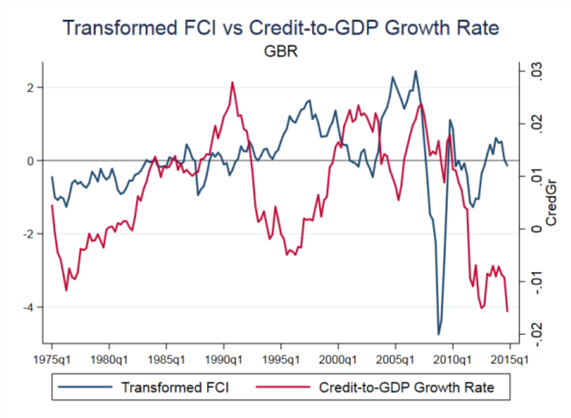
Country	Start date for estimation	Interbank Spread	Corporate Spread	Sovereign Spread	Term Spread	Equity Returns Volatility
AUS	1975q1	1979q1	1983q2	1973q1	1979q1	1973q1
CAN	1981q2	1973q1	1979q1	1973q1	1973q1	1973q1
CHE	1980q2	1980q1	1982q1	1979q1	1980q1	1973q1
DEU	1975q1	1979q1	1977q1	1977q1	1979q1	1973q1
ESP	1992q1	1990q1	1990q1	1990q1	1990q1	1990q1
FRA	1980q3	1979q1	1979q1	1977q1	1979q1	1973q1
GBR	1975q1	1973q1	1979q1	1973q1	1973q1	1973q1
ITA	1981q2	1979q1	1979q1	1977q1	1979q1	1973q1
JPN	1975q3	1979q1	1973q1	1973q1	1979q1	1973q1
SWE	1980q2	1979q1	1979q1	1979q1	1979q1	1973q1
USA	1975q1	1973q1	1973q1	1973q1	1973q1	1973q1

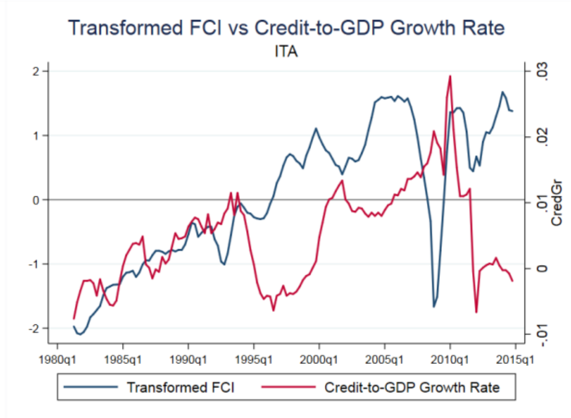
Country	Equity Returns	Change in real long - term rate	Change in FX	VIX	MOVE	House price return
AUS	1973q1	1973q1	1970q1	1986q1	1988q2	1973q1
CAN	1973q1	1973q1	1970q1	1986q1	1988q2	1973q1
CHE	1973q1	1979q1	1970q1	1986q1	1988q2	1973q1
DEU	1973q1	1977q1	1971q1	1986q1	1988q2	1973q1
ESP	1990q1	1992q1	1971q1	1986q1	1988q2	1990q2
FRA	1973q1	1973q1	1971q1	1986q1	1988q2	1973q1
GBR	1973q1	1973q1	1970q1	1986q1	1988q2	1973q1
ITA	1973q1	1973q1	1971q1	1986q1	1988q2	1973q1
JPN	1973q1	1973q1	1970q1	1986q1	1988q2	1973q1
SWE	1973q1	1979q1	1970q1	1986q1	1988q2	1973q1
USA	1973q1	1973q1	1970q1	1986q1	1988q2	1973q1

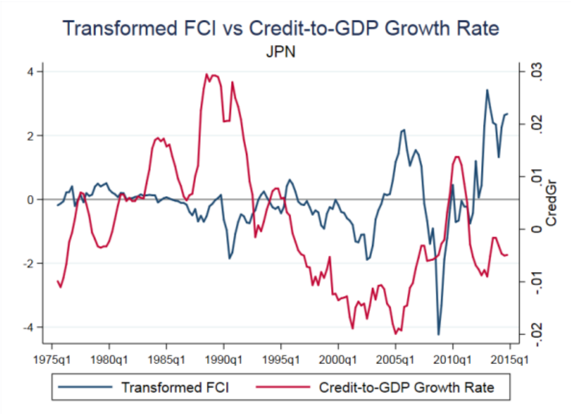
Country	Change in equity market capitalization of financial sector to total market	Domestic commodity price inflation	Equity trading volume	Market capitalization for equities	Market capitalization for bonds	Expected default frequencies for banks
AUS	2000q1	1970q1	1994q2	2001q1	1995q4	1999q4
CAN	2000q1	1970q1	1990q4	2000q3	1995q4	1999q4
CHE	2000q1	1970q1	1994q2	2002q4	1995q4	1999q4
DEU	2000q1	1970q1	1993q4	1973q4	1995q4	1999q4
ESP	2000q2	1970q1	1992q4	2001q2	1995q4	1999q4
FRA	2000q1	1970q1	1993q4	1988q4	1995q4	1999q4
GBR	2000q1	1970q1	1993q4	1986q4	1995q4	1999q4
ITA	2016q1	1970q1	2004q2	2004q2	1995q4	1999q4
JPN	2000q1	1970q1	1993q4	1989q4	1995q4	1999q4
SWE	2000q1	1970q1	1993q4	2001q2	1995q4	1999q4
USA	2000q1	1970q1	1990q4	2001q2	1995q4	1999q4

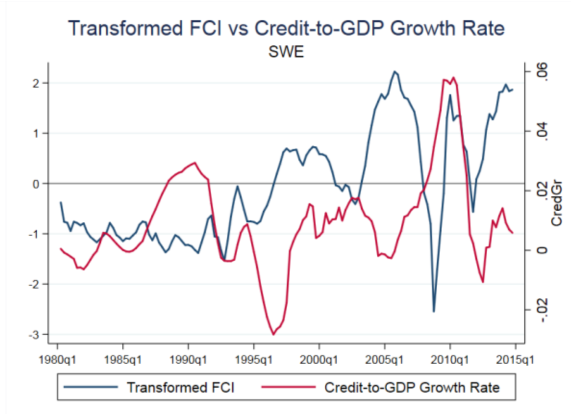
Appendix B: FCI and credit-to-GDP growth

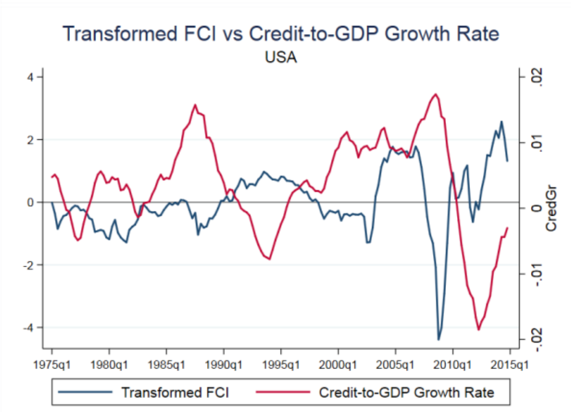



Transformed FCI vs Credit-to-GDP Growth Rate
GBR
2
0
-2
-4
.03
.02
.01
0
-.01
-.02
CredGr
1975q1
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1
Transformed FCI
Credit-to-GDP Growth Rate


Transformed FCI vs Credit-to-GDP Growth Rate
ITA
2
1
0
-1
-2
.03
.02
.01
0
-.01
CredGr
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1
Transformed FCI
Credit-to-GDP Growth Rate


Transformed FCI vs Credit-to-GDP Growth Rate
JPN
4
2
0
-2
-4
.03
.02
.01
0
-.01
-.02
CredGr
1975q1
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1
Transformed FCI
Credit-to-GDP Growth Rate


Transformed FCI vs Credit-to-GDP Growth Rate
SWE
2
1
0
-1
-2
-3
.06
.04
.02
0
-.02
CredGr
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1
Transformed FCI
Credit-to-GDP Growth Rate


Transformed FCI vs Credit-to-GDP Growth Rate
USA
4
2
0
-2
-4
.02
.01
0
-.01
-.02
CredGr
1975q1
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1
Transformed FCI
Credit-to-GDP Growth Rate