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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 find 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. In addition, the term structure of GaR features an intertemporal tradeoff: When initial financial conditions are loose, GaR is higher in the short run but lower in the medium run, and the tradeoff is amplified by a credit boom. This shift in the conditional GDP growth distribution violates the common modeling assumption that the mean and variance are independent, which suggests that models with macrofinancial linkages that do not incorporate the endogeneity of higher-order moments may systematically underestimate downside risks to GDP growth in the medium run.

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1. Introduction

Financial conditions affect the distribution of predicted GDP growth, 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 mean growth 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 term structure of the distribution of predicted 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 predicted real GDP growth conditional on financial conditions—which we call growth-at risk (GaR)—and then how GaR changes over a projection horizon of twelve quarters. Concretely, GaR as the conditional growth at the (lower) 5th percentile of the GDP growth distribution captures predicted growth at a low realization of the GDP growth distribution. Intuitively, higher predicted median GDP growth and lower volatility would lead to a higher GaR, and lower median and higher volatility would lead to a lower GaR. By also estimating its 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 using quantile regressions. We expand on Adrian, Boyarchenko, and Giannone (2019) estimates by adding credit growth, applying the model to 11 AEs, and extending the term structure beyond the near-term to the medium-term of twelve quarters. 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 downside risk over the forecast horizon.

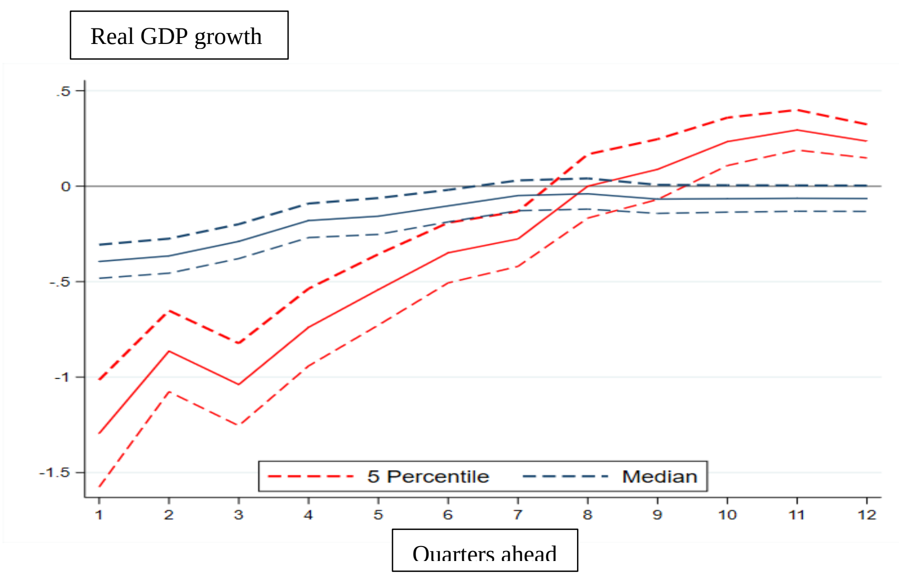
Figure 1 provides an illustration of the important role of financial conditions (FCI) for the modeling of the distribution of growth and the implied intertemporal risk-return tradeoff. In particular, coefficient estimates on the financial conditions index (FCI) from panel quantile regressions differ significantly 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). The FCI for each country is based on up to 17 price-based variables, including short-term interbank risk spreads, corporate bond spreads, and volatility of stock returns. They are estimated, following Koop and Korobilis (2014) using a

[1] The 11 AEs include Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, Sweden, and the US.

vector autoregression model with time-varying parameters which takes into account changes in the interaction of the financial variables and the macroeconomy and differences in data availability of the variables.[2]

The negative coefficients on FCI 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.[3] But the increase in coefficients over the projection horizon suggest the impetus from initial looser financial conditions will decline or subtract from median forecasted cumulative growth in quarters further out, at about nine quarters and more. The increase is more pronounced for the 5th percentile than the median and illustrates the shifting forecasted growth distribution over the projection horizon. The significant reversal from negative to positive in 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 median and 5th percentile of real GDP growth



Note: The figure plots 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. Real GDP growth is measured in percent. Higher FCI represents tighter 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.

[2] The components of FCI are listed in Appendix A and the FCI series for each country are plotted in Appendix B.
[3] We use the term "expected growth" to refer to the forecasted median growth, our measure of central tendency.

Our interpretation of these coefficients is that changes in the distribution of GDP growth over the projection horizon reflect changes in the price of risk from initial conditions. Changes in the price of risk can arise from financial frictions, such as regulatory capital constraints or VaR models used for risk management, which tie together the price of risk and volatility via the credit supply of financial intermediaries (Adrian and Shin, 2014; He and Krishnamurthy, 2012, 2013). If financial conditions initially are loose (asset prices are high), constraints are less binding, and GDP growth is higher and its distribution is tighter. However, the low price of risk and low volatility can contribute to greater risk-taking by financial intermediaries and higher vulnerabilities, which leaves the economy prone to a sharper rise in volatility in the event of a negative shock, consistent with the volatility paradox of Brunnermeier and Sannikov (2014).

We also allow for nonlinear effects of FCIs on the growth distribution through financial vulnerabilities that could amplify a negative shock. In particular, we include the growth of nonfinancial sector credit-to-GDP and a credit boom indicator variable defined by when both financial conditions are loose and credit-to-GDP growth is rapid. High borrower credit can be an amplification mechanism when there is asymmetric information and thus an external finance premium (Bernanke and Gertler, 1989, and Bernanke, Gertler, and Gilchrist, 1999). When asset prices and borrower net worth fall, lending spreads rise and borrowing falls disproportionately. Rapid 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). The estimated coefficients on the credit boom indicator variable suggests that a credit boom forecasts significantly lower GaR in the medium term than when just financial conditions are loose.

The estimations indicate meaningful differences in the term structure of GaR depending on the initial level of financial conditions. A key result is that GaR conditional on initial loose FCI and a credit boom is significantly higher in the near-term and significantly lower in the medium-term than GaR conditional on average FCI. Specifically, when FCIs are loose (in the bottom 10 percent), GaR in the near-term is about 0.5 percent, and then declines substantially to less than -2 percent in the medium-term, while the GaR for average FCI (defined by the middle four deciles) increases moderately from -2.5 percent over the projection horizon.

A second key result is that greater downside risks to growth in the medium-term are not counterbalanced by higher expected growth. While expected growth from loose FCI and high credit growth is modestly higher relative to average initial FCI in the near-term, about 0.5 percentage points higher, the difference falls and becomes negative over the projection horizon, while GaR falls much more sharply.

We present results using a granular instrumental variables (GIV) approach put forth recently by Gabaix and Koijen (2019) to assess the extent to which potential endogeneity bias between financial conditions and GDP growth may be a reason for these empirical results. A concern is that the FCI could reflect shocks more quickly than real variables such as GDP growth, and the empirical patterns we estimate simply reflect the delay. To apply the GIV method to construct an instrument for financial conditions, we use an expected default frequency (EDF) index for financial firms in place of the FCI because firm-level data, which are necessary for the GIV method, are available. We show that the coefficients on an instrumented financial firm EDF index exhibits the same properties as the coefficients on FCI, namely that they switch signs over the projection horizon and give rise to a similar term structure for GaR. These results using the GIV technique based on firm-specific EDFs are consistent with a causal effect of financial conditions on GaR, and thus against potential endogeneity bias as a reason for the intertemporal patterns in GaR.

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.

In other robustness tests, we use corporate bond spreads instead of FCI and find that coefficients on corporate bond spreads show a similar pattern to those for the FCI on the 5th percentile, with more narrow spreads associated with lower downside risks in the near-term but greater downside risks in the medium-term. But the effects of the FCI after corporate bond spreads also are included remain significant, which suggests that variables in the FCI other than corporate bond spreads are relevant to the predicted growth distribution.

We also disaggregate nonfinancial credit into nonfinancial business and household credit, but do not find that one type of credit is driving the results. In addition, we show the sensitivity of GaR estimates when excluding the global financial crisis, either by replacing 2008 and 2009 values with averages based on 2007 and 2010 data or eliminating the 2005 through 2009 period. The GaR estimates continues to show a tradeoff, though it is less steep, as expected, once this significant episode with large negative growth is excluded. Finally, results from applying this model to only the US are similar to results for our sample of AEs. We also show for the US that our results of an inter-temporal risk tradeoff are robust to controlling for monetary policy, consistent with our results reflecting changes in the price of risk.

The empirical results in this paper have important implications for macroeconomic models. 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 higher-order moments and the implications that such endogeneity may have for projections.

The intertemporal tradeoff illustrated by the term structure of GaR could also have implications for policymaking, although the empirical results are not treatment effects, notwithstanding the granular instrumented variables analysis that provides evidence for causality. 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 future financial systemic risks 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 (2019), 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 estimate 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 a panel of 11 advanced economies (AEs). In particular, we estimate conditional distributions of GDP growth for near-term and medium-term horizons, defined roughly as one-to-four quarters ahead and five-to-twelve quarters ahead, respectively. We allow for nonlinearities from financial vulnerabilities, measured by the interaction of high credit-to-GDP growth and loose financial conditions. The 11 AEs represent a set of countries that are defined by the IMF to have systemically important financial sectors and for which we have sufficient data for estimation.

a. Model estimation with quantile regressions

The estimates of the conditional predicted 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 quarters *t* and *t+h*, and $x_{i,t}$ a vector of conditioning variables. The conditioning variables in $x_{i,t}$

include current GDP growth, inflation, FCI, private nonfinancial credit-to-GDP growth, a dummy variable for credit boom, defined by the interaction of loose FCI and high credit growth, and a constant.[4]

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

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

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

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 illustrate that the choice of 5 percent as the cutoff is a reasonable representation of the lower tail.

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 (see Jorda (2005) and Stock and Watson (2018)), while at the same time having a model that

[4] We estimate conditional quantile regressions (CQR), although we note the evolving literature on so-called 'unconditional' quantile regressions (UQR). Originally proposed by Firpo, Fortin and Lemieux (2009), application of UQR is conducive to inference in cross-sectional regression settings to understand, for instance, the effect of a marginal change in workers' characteristics on each quantile of the overall distribution of individuals' wages. In such a case, unconditional quantiles of two individuals with different education levels would be their wage quantiles among all individuals in the population. In our case, given we seek to generate forecast distributions corresponding to a single target variable (GDP growth) over time conditional on a set of determinants, rather than information pertaining to a set of distinct individuals, CQR is the appropriate framework.

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, although we provide below some empirical support for causal effects. For simplicity, we will refer to the former as "effects" in the discussion that follows.

We estimate the model in a panel regression with country fixed effects. The estimated parameters on FCIs and the other independent variables represent average behavior across each set of countries at each horizon *h*.

Estimation of the panel quantile regressions with quantile-specific country fixed effects is feasible when the panel structure has *T* (the time series dimension) much larger than *N* (number of countries), as is the case in our forecasting application (Galvao and Montes-Rojas, 2015, and recently Cech and Barunik, 2017).[5] Inferential procedures based on bootstrap resampling 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.[6] In the analysis below, we generate bootstrap standard errors considering block widths of 4, 6 and 10 quarters, but report only block widths of 4 quarters as results are quite similar. All standard errors estimates are based on 10,000 bootstrap samples.

Below we generally report the direct estimates from the quantile regressions for the 5th, 50th, and 95th percentiles, rather than estimates from a smoothed distribution. However, we also show probability density functions which we recover by mapping the quantile regression estimates into a skewed t-distribution, following Adrian et al (2019), which allows for four time-varying moments – conditional mean, volatility, skewness, and kurtosis. To do so, we fit the skewed *t*-distribution developed by Azzalini and Capitaion (2003) in order to smooth the quantile function:

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

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

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 tightening 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 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), and the forecasting power of the nonfinancial credit-to-GDP gap for recessions in cross-country estimations (Borio and Lowe, 2002). This linkage is also supported directly in a VAR model of the US, where the interaction of financial conditions and a high nonfinancial credit-to-GDP gap lead to higher future volatility of GDP (Aikman, Lehnert, Liang 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 in country *i* as:

(5) $$\lambda_{i,t}=\begin{cases}1 & \text{if FCI and } \Delta\text{Credit-to-GDP are in their bottom and top 3 deciles, respectively} \\ 0 & \text{else}\end{cases}$$

Growth in the private nonfinancial credit-to-GDP ratio is measured over the previous eight quarters. We define $\lambda_{i,t}$ when FCI is in the bottom three deciles of its distribution (lower FCI represent looser financial conditions) and credit-to-GDP growth is in the top three deciles of its distribution. 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 than in the near-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 the price of risk rises and 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.[8] 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 (higher GaR) 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 loose 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). 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). Gennaioli and Shleifer (2018) interpret lower price of risk and greater risk-taking as a result of beliefs that extrapolate the past and that neglect downside risks. Extrapolation can explain why the price of risk can be very low for prolonged periods. Neglected downside risks can explain how financial systems can become highly leveraged as agents lever up when they share beliefs that the price of risk is unlikely to increase sharply and that other agents are somehow protected from negative shocks.

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[7] We choose the bottom three deciles for FCI 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 bottom two deciles or third of the FCI distribution, but the dummy variable would then cross-over deciles and complicate the presentation.

[8] The addition of credit growth also helps to address the possibility 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 growth. The significance of the credit boom variable also supports the GIV results presented below.

In addition, lower risk premia may be associated with exuberant sentiment, and Greenwood and Hanson (2013) show 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.

Our empirical model can be interpreted within the setting of Adrian and Duarte (2018) where financial frictions in an otherwise standard New Keynesian setting gives rise to time variation in the market price of risk and, as a consequence, in GDP growth. In their model, optimal monetary policy depends on financial conditions in addition to inflation and the output gap because, as in the data, financial conditions predict GaR in the year-ahead even after controlling for inflation and the output gap. Adrian, Duarte, Grinberg, Mancini-Griffoli (2017) expand this approach to a cross-section of advanced and emerging market economies. This paper expands to the term structure of GaR out to twelve quarters for a cross-section of advanced economies and finds an intertemporal tradeoff for initial loose financial conditions which is amplified by a credit boom. Adrian, Duarte, Liang, and Zabczyk (2019) offer a simple quantitative extension to a New Keynesian model to include a financial accelerator and endogenous volatility to match the term structure of GaR, and to develop implications for monetary and macroprudential policies.

3. Data

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).[9] Nonfinancial credit-to-GDP ratios and its components, household and nonfinancial business, are from the BIS.

We construct FCIs for each of the 11 countries using up to 17 price-based variables.[10] The FCI captures domestic and global financial price factors, such as corporate bond risk spreads, equity returns and

[9] Estimates of potential growth for the 11 countries are not available on a consistent basis, or for the full sample periods.
[10] 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.

volatility. Data availability varies across the countries, 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) which builds on the estimation methodology of Primiceri's (2005) time-varying parameter vector autoregression model and dynamic factor model of Doz, Giannone, and Reichlin (2011). This approach has two benefits: (i) it allows for dynamic interactions between the FCIs and macroeconomic conditions which can evolve over time, and which suggests the measure is not contaminated by contemporaneous macro effects, and (ii) it allows for a flexible estimation procedure that can deal with some financial indicators being available for different time periods.

The model for FCI 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 3.6 percent. The average credit-to-GDP ratio is 1.34 and the eight-quarter moving average growth in the ratio is 0.54 percent, indicating credit grew faster than GDP on average through the sample period. Periods when the credit boom λ is equal to 1 are 8.0 percent of sample. We then can observe how a configuration of loose FCIs with positive credit-to-GDP 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 multiple quarters ahead, suggesting credit responds to FCI with a lag. 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, output growth, credit growth, and credit boom λ. First, we show the time series of GaR averaged across countries at a given projection horizon and show there is greater variance in downside than in upside risks. Second, we show the probability density functions of forecasted 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 there is a credit boom. 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 projected conditional 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 a credit boom project higher expected median growth and GaR in the near-term, the median differential declines modestly while the decline in the GaR differential is substantial, suggesting sharp increases in downside risks without the benefit of higher growth. These results expand on Adrian et al (2019) by demonstrating the results for a panel of 11 AEs and including a credit boom interaction. For comparison, we present below the time series results for the US only (see Section 5d, Figure 13a).

a. Estimated FCI coefficients with interaction

Figure 1 shown above presents the estimated coefficients on FCI, where lower FCI represents looser financial conditions (lower price of risk). As discussed above, coefficients for the 5^{th} percentile 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 low downside risk at short horizons, which set the stage for a deterioration in performance three years later.[11]

Figure 2 shows the coefficients on λ for the 5^{th} percentile quantile regressions over the projection horizon. 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).

The significant coefficients for credit boom λ are consistent with macrofinancial linkages that can lead to variation in the distribution of forecasted 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 also expect larger costs because growth in credit is higher. 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

Figure 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 95^{th} 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 95^{th} percentile, suggesting greater variability for downside risk than upside risk.

In particular, the mean GaR for AEs over the sample period is -1.22 percent, with a standard deviation of 1.23, whereas the standard deviation of the 95^{th} percentile is lower at 0.36, even though the mean 95^{th} percentile is much higher, at 5.25 percent. Basically, the conditional 95^{th} percentile shows little variation,

[11] This key result is robust to not including credit growth or its interaction with FCI, and other alternatives as discussed below in Section 5.

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.

c. Probability density functions of forecasted 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 GaR as well as the tails, and the dynamics of the term structure.

The projected growth distribution conditional on loose FCI (bottom 1 percent) and credit boom for $h = 3$ is fairly tight and has very little mass in the left tail (figure 4a). In contrast, the distribution at $h = 8$ for the same initial loose FCI and credit boom is wider and has much more mass in the left tail. These distributions indicate substantial shifts and increased downside risks from h=3 to h=8 when initial financial conditions are loose in a credit boom. For loose FCI but without a credit boom, the distribution also shifts between h=3 and h= 8, but the shift is less pronounced, suggesting GaR has fallen only moderately (figure 4b).[12]

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 groups to evaluate if loose FCI is more likely to have both lower risk in the near-term and higher risk later. We show the GaR term structure estimates based on initial average FCI values for four groups: in the bottom 1 percent (very loose financial conditions), bottom decile (loose financial conditions), top decile (very tight financial conditions), and middle 40 percent, and by whether credit boom λ is equal to zero or one.

The term structures indicate an intertemporal tradeoff for downside risk when initial FCIs are loose, and the tradeoff is more substantial if there is also a credit boom. When initial FCIs are in the bottom decile or bottom 1 percent, the estimated GaRs are initially high but then fall over most of the projection

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[12] 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 loose FCI and a credit boom. Without a credit boom, the probability of negative growth rises more modestly from zero to about 9 percent for loose FCI.

horizon, indicating downside risks increase in the medium-term; the downward slope is much sharper when there is also a credit boom (figure 5a) relative to when there is not (figure 5b). Specifically, GaR is about 1 percent in the near-term for very loose FCIs (Bot 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 bottom decile (Bot 10) is about 2.5 percent. We use the four middle deciles (labeled Mid 40) of initial FCI values to represent "typical" moderate conditions, to approximate for expected growth and downside risk when FCIs are neither high nor low. Estimated GaRs for initial FCI in the mid-range (Mid 40) rise initially and then level out at about -0.5 percent in the medium-term. That is, the term structure for the typical moderate FCI group slopes upward rather than downward, as moderate FCIs do not increase downside risks to growth in the medium-term.[13]

To compare the differences in the GaR term structures, we calculate the differences between the Bot 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 Bot 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 Bot 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 top decile (Top 10). GaR for this 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 converge in the medium term to about the same GaR as for initial moderate financial conditions. We view very tight FCIs as reflecting the realization of a negative shock, which leads 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

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

sharper tightenings in FCIs once a negative shock occurs (Brunnermeier and Pedersen (2009), Brunnermeier and Sannikov (2014), and Adrian and Shin (2014)). Or sharper 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 predicted median growth and GaR by initial FCI groups

So far, we have focused on GaR, the lower 5th percentile of the forecasted growth distribution. But a drop in the 5th percentile from initial loose FCIs could also be accompanied by higher expected growth, 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 forecasted additional expected growth conditional on loose FCI 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 Bot 10 and Mid 40 FCI groups, with and without a credit boom (figures 7a and 7b). First, median growth is a bit higher in the near-term for FCI in the Bot 10 than for Mid 40 in both cases, and then falls over the projection horizon. That is, the marginal contribution to growth from loose FCI diminishes over the projection horizon. Second, GaR is higher (downside risk is lower) for FCI in the Bot 10 than for Mid 40 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 bottom 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 for the loosest FCI group relative to typical FCIs. 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.

f. Applying granular instrumental variables to evaluate causality

In this section, we exploit the Granular Instrumental Variable (GIV) methodology (Gabaix and Koijen, 2019) to evaluate a possible causal effect of financial conditions on GaR. To implement this, we approximate financial conditions with a country-specific aggregate index of the expected default frequencies (EDFs) of financial institutions, a market-based measure of credit risk based on a distance to default model. [14] Like financial conditions indexes and corporate bond spreads, it is viewed to have predictive power for economic growth and risks to growth. We use EDFs as an alternative measure for financial conditions because we have firm-specific EDFs necessary to use the GIV method and construct an instrument.[15]

The GIV method exploits the variability of the underlying firm-level data and its heterogeneous size distribution to construct a valid instrumental variable for aggregate data. When there are agents that are large enough (that is, they are "granular"), their idiosyncratic shocks will have an aggregate impact. Gabaix and Koijen show that this distribution allows a valid and optimal instrumental variable to be constructed for the aggregate data. The exclusion restriction is that aggregate shocks to each country's aggregate EDF index are uncorrelated with idiosyncratic shocks to financial institutions' EDFs.

The financial institutions' EDFs are from Moody's and are calculated based on a firm's assets, liabilities, and the market value and volatility of its equity. We use market capitalization also from Moody's to construct each financial institution's share in the country-level EDF. Importantly, these shares show an important degree of concentration, which is needed for the GIV approach to be valid. We use quarterly series from their starting point in 1999:Q4 to 2015:Q4. We drop the institutions for which the data series is too short (either because it starts late or because it disappears from sample). For France and Spain, we are left with only two firms per country, so we drop these countries from the sample. The resulting sample includes nine countries for which we have at a minimum of six firm-level EDFs covering the whole period, with five of those countries having many more firms and representing complex and larger financial systems.

[14] EDF is a measure of the probability that a firm will default over a specified period of time. "Default" is defined as failure to make scheduled principal or interest payments. According to the Moody's EDF model, a firm will default when the market value of its assets (the value of the ongoing business) falls below its liabilities payable (the default point).

[15] Note that individual financial firm level measures for comparable corporate bond spreads, for example, are very difficult to get for the countries in our sample.

The GIV method relies on recovering idiosyncratic shocks for individual financial institutions EDFs by filtering common factors. We apply the GIV methodology in the following way.[16] First, for each country we use the individual financial institutions' EDFs and market capitalization shares and construct an aggregate EDF index. Second, we apply principal component analysis (PCA) to the individual series and use an optimal number of principal components. Third, the resulting idiosyncratic errors from the PCA estimation and market capitalization shares are then used to construct the GIV as in equation (24) in Gabaix and Koijen.[17] Finally, we use the GIV to instrument the aggregate EDF indexes in the quantile panel estimation with local projections for GDP growth (equation (1)), where EDF replaces FCI. Because EDF data are available for a shorter time period than FCI, we estimated our model for a shorter time period, starting in 1999:Q4 rather than in the mid-1970s. In addition, because of the much shorter sample period, we do not include credit-to-GDP growth and the "credit boom" interaction term as the resulting estimation for those variables becomes too noisy.

The estimations show that the instrument is relevant, with a first-stage F-test of 29 and the coefficient on the GIV is significant at 5 percent level. Moreover, the instrumented EDF provide evidence that looser financial conditions (lower EDF) have a *causal* effect in the compression of downside risks in the near term and then an increase in downside risks in the medium term.

Figure 9a shows both the estimated causal marginal effect of aggregate EDF on the 5th percentile and the estimation without instrumenting EDF. The estimated effects for the financial firm EDF index are significant and show the same pattern as when estimating the model based on FCI. The estimated effects for the instrumented EDF index also are significant, providing strong evidence against endogeneity bias and in favor of causality to explain the empirical results. Moreover, the estimated effects suggest that the non-causal effects have an attenuation bias, because the estimated coefficients for the 5th percentile are substantially greater when the EDF is instrumented than when it is not.

Figure 9b shows the resulting term structure of GaR for different initial EDF groups from the GIV method. The results are very similar to those highlighted earlier based on initial FCI but the magnitudes of the tradeoffs are smaller, reflecting a different estimation period and without a credit boom interaction. Nonetheless, the GIV of the financial firm EDF shows looser financial conditions (Bot 10) reduce downside risk in the near-term but then increase downside risks in the medium-term relative to average financial conditions (Mid 40).

[16] This application of GIV to a panel with local projections follows closely Aldasoro et al (2019). The main difference is that here we estimate a quantile panel rather than a model for the conditional mean.

[17] We take a conservative stance on the appropriate number of factors and use the ones with eigenvalues above the unit.

g. 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, notwithstanding the results from the GIV method above, the increased downside risks in the medium-term associated with looser financial conditions (lower price of risk) suggests that policymakers might want to consider intertemporal risk tradeoffs.

An important consideration, conditional on this intertemporal tradeoff, is whether the higher future downside risks are substantial enough to want to forego the slightly higher expected median growth and 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 worker 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, starting with an alternative two-step OLS estimation of mean and variance rather than quantile estimates, and find very similar results. We then present results for specifications using a corporate bond spread, disaggregating nonfinancial credit, and excluding the Global Financial Crisis. We find that the intertemporal risk tradeoffs remain, although GaR estimates are not as low as when we include the more extreme negative growth outcomes. We also report results specifically for the US, and show results are similar to Adrian et al (2019) and robust to a slightly different empirical model and different FCIs. The US results also are robust to adding monetary policy, showing that the effects of financial conditions on GaR are a consequence of changes in the price of risk and 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:

$$(8)\quad \Delta y_{i,t+h} = \gamma_0^{(h)} + \gamma_1^{(h)} f_{i,t} + \gamma_2^{(h)} \Delta g_{i,t} + \gamma_3^{(h)} \Delta y_{i,t} + \gamma_4^{(h)} \pi_{i,t} + \gamma_5^{(h)} \lambda_{i.t} + \varepsilon_{i,t} \qquad h = 1, \dots, 12$$

$$(9)\quad \ln \hat{\varepsilon}_{i,t+h}^2 = \beta_0^{(h)} + \beta_1^{(h)} f_{i,t} + \beta_2^{(h)} \Delta g_{i,t} + \beta_3^{(h)} \Delta y_{i,t} + \beta_4^{(h)} \pi_{i,t} + \beta_5^{(h)} \lambda_{i,t} + v_{i,t} \qquad h = 1, \dots, 12$$

where $\Delta y_{i,t+h}$ is the average GDP growth rate between quarter *t* and *t*+*h* for country *i*, $f_{i,t}$ is the FCI, $\Delta g_{i,t}$ is the eight quarter moving average of the growth rate in private nonfinancial credit-to-GDP, $\pi_{i,t}$ 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 $\ln \hat{\varepsilon}^2_{i,t+h}$ onto the right-hand side variables of equation (9). 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.[18] Standard errors are computed using Newey West standard errors that correct for the autocorrelation in the error term generated by the local projection method (see Jorda (2005) and Ramey (2016) for a discussion of standard errors for local projection regressions).

GaR, the forecasted conditional growth in the lower (left) tail of GDP growth distribution, is computed as:[19]

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

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 projected 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 projected volatility at period *t*+*h*, which is equal to the square 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 set to 5 percent, thus capturing the left tail of GDP growth in the 5th percentile of its conditional distribution.

Estimated coefficients on FCI for forecasted growth and volatility support the results from the quantile regressions. The coefficients for growth are negative in the near-term but increase over the projection horizon (figure 10a). At the same time, the coefficients for volatility are positive in the near-term and decrease over the projection horizon (figure 10b). That is, loose 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 11 is the counterpart to figure 5, which was based on the quantile estimations.

[18] Given the assumption of a conditional Gaussian distribution, the estimated mean and variance are sufficient to describe the unconditional distribution of future GDP growth.
[19] Adrian and Duarte (2018) show that for a low value of α this is a good approximation as higher order terms go rapidly to zero.

The term structures of the GaR from the two-step estimation procedure with assumed Gaussian distributions have very similar shapes to the GaR from the quantile estimations, indicating qualitative results are robust to alternative estimation methods. The GaR estimates are higher with the two-step procedure because of the stronger distributional assumptions under the two-step method. The quantile approach is less constraining on the variance and GaR estimates since it is semiparametric and allows for more general assumptions about the functional form of the conditional GDP distribution. Still, the implied cross-sectional distinctions based on initial FCI from the simpler-to-implement two-step procedure are consistent with the existence of a substantial intertemporal risk tradeoff found with the quantile regressions.

b. Other financial indicator and credit variables

The results reported above are for a specific FCI constructed for each country based on Koop and Korobilis (2014). A FCI has an important advantage of providing a parsimonious indicator of financial conditions, and the Koop and Korobilis method allows the weights for different indicators to change over time based on their significance with the macroeconomy, and for differences in data availability of individual indicators. Given the predicted negative effects of the excess bond premium and corporate bond spreads on expected growth (Gilchrist and Zakrajsek, 2012), we evaluate whether corporate bond spreads can help to predict the 5th percentile of predicted GDP growth. We find that coefficients on corporate bond spreads for the 5th percentile show the same pattern as coefficients on the FCI, which show that loose credit spreads are associated with a tighter left tail in the near-term, but a wider left tail in the medium-term (figure 12, panel a). However, coefficients on FCI are largely unchanged when corporate bond spreads are also included separately. These results suggest financial variables other than corporate bond spreads are relevant. [20] While it would be possible to include simultaneously many separate financial indicators to distinguish possible effects, we would lose the efficiency of a parsimonious index and a single interaction term with growth in credit-to-GDP.

We also look at whether either business or household credit contributed disproportionately to the term structure of GaR. Some studies have found that household mortgage credit is an especially significant predictor of slow growth (Mian et al, 2015), and we can test whether it has a similarly important effect for

[20] We tried a similar exercise for equity return volatility and the change in the exchange rate, and while the credit boom variable based on equity return volatility for the 5th percentile was significant, coefficients for median and 5th percentile of output growth were not as significant as for corporate bond spreads, and FCI coefficients remained highly significant after these variables also were included. In addition, the results above for a financial firm EDF index, which also were significant, cannot be compared directly because there is more limited data and those estimations are based on a shorter time period, fewer countries, and a model without a credit interaction term.

the left tail of the growth distribution. For our panel of 11 countries, we do not find significant differences for the GaR term structure between the effects of household and business credit and, if anything, the effect of the credit boom is driven more by business credit than household credit (results not shown, available on request). This result may not be too surprising for our sample of advanced economies since the mid-1970s, which had many more business credit cycles than household real estate booms before the GFC.

c. Quantile estimates excluding the Global Financial Crisis

The global financial crisis was a significant event, the largest in advanced economies since the Great Depression. Including that episode with loose financial conditions and rapid credit growth, followed by a massive tightening of financial conditions and credit, and a deep recession has a significant effect on the estimates. We show the sensitivity of the results to the GFC with two alternative ways to exclude the GFC. While results after excluding the most negative outcomes are weaker, as expected, the term structure of GaR remains, albeit with less steep tradeoffs. First, we drop from the sample the years 2008 to 2009 and replace values in those years with averages of the variables at the beginning and end of the excluded period. The results indicate the corresponding GaR term structures for initial loosest FCI groups (Bot 1 and Bot 10) continue to slope downward, though the slope is less steep (figure 12b). We interpret these results as indicating that the estimated GaR reflect a general relationship between financial conditions and the distribution of forecasted growth over many decades, since the mid-1970s, but the results are strengthened when the GFC is included in the estimation.

We also estimate the regressions using data excluding the years 2005 through 2009, which excludes the most rapid build-up phase to the GFC and the accompanying recession. We re-define the credit boom variable to be the intersection of the loosest two deciles for FCI and fastest two deciles of nonfinancial credit-to-GDP growth, rather than based on three deciles for both, because the wider three-decile band for the sample excluding the GFC leads to a credit boom variable that includes very normal periods. Coefficients on FCI exhibit a similar but weaker pattern than for the full sample, and GaR is not as high for the loosest decile and not as low for the tightest decile in the near-term, though an inter-temporal tradeoff for GaR remains (figure 12c).

d. US estimates

For comparison to Adrian et al (2019), we show the results from our empirical model for the US only. The model in this paper differs because we include inflation, credit growth, and a credit boom dummy variable. Results shown for *h*=4 from the quantile estimations based on just the US data show greater variability for downside risk than upside risk, as the case based on all 11 AEs (figure 13a). The estimates for the US clearly illustrate the intertemporal risk tradeoff (figures 13b and 13c). While the estimated GaR is higher for the US than for AEs on average, the term structures for Bot 1 and Bot 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 (2019), and demonstrate the results are robust to different FCIs and modest changes in the empirical model.

We also test for the possibility that the observed effects of FCI on GaR for the US reflect monetary policy rather than the price of risk in financial conditions. 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 distribution of future GDP growth. 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-estimation does not significantly change the adjusted FCI, likely because we already controlled for output growth and inflation in the estimation of the original FCI. We then add residuals of the policy rate from a Taylor rule specification to the quantile regressions for the US, while using the re-estimated FCI. Residuals are based on the original specification of the Taylor rule from the St. Louis FRED database.[21]

The estimated coefficients on the adjusted FCI for the 5th percentile of projected growth after adding the residuals are very similar to those in our original specification, positive at near-term horizons and switching to negative in the medium-term (figure 13d). The corresponding GaR estimates from the model with the addition of the Taylor rule residuals differ modestly from estimates without the residuals, but importantly continue to show a significant intertemporal risk tradeoff exists (figure 13e). These results for the US indicate the estimated effects of FCI on the GaR term structure are not a result of not including monetary policy in the empirical model.

[21] 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 as in https://www.frbatlanta.org/cqer/research/taylor-rule.aspx?panel=1. Results shown with the Taylor rule residuals are based on estimations that exclude credit because some variables lose statistical significance with the larger set of explanatory variables when estimations are for a single country, the US, rather than the full panel of AEs.

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 financial conditions and the distribution of real GDP growth for 11 AEs from 1975 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 forecasted growth, and we focus on the lower 5th percentile of forecasted growth for horizons out to twelve quarters, which measures the term structure of growth-at-risk.

The main contributions of this paper are to show empirically that financial conditions affect the distribution of predicted GDP growth, and its effects change over the projection horizon, consistent with an intertemporal risk 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 based on panel estimates for 11 AEs that financial conditions have strong forecasting power for the distribution, not just the mean, of forecasted growth, and that the signs of the coefficients on financial conditions reverse from the short to medium term horizons for the lower tail of the distribution. Combined, the conditional projected growth distribution shifts with changes in financial conditions, with the lower tail, GaR, more responsive than the median or upper tail to financial conditions. Results using a GIV method suggest these results are not due simply to endogeneity bias.

Of particular significance, looser financial conditions imply higher GaR in the near-term, but these effects reverse and imply a lower GaR (higher downside risk) in the medium-term relative to outcomes from initial moderate financial conditions. Moreover, the additional boost to forecasted growth from initial loose financial conditions and high credit diminishes over the projection horizon, suggesting that forecasted 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 could 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 forecasted 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 the severity of stress test scenarios, a countercyclical capital buffer, 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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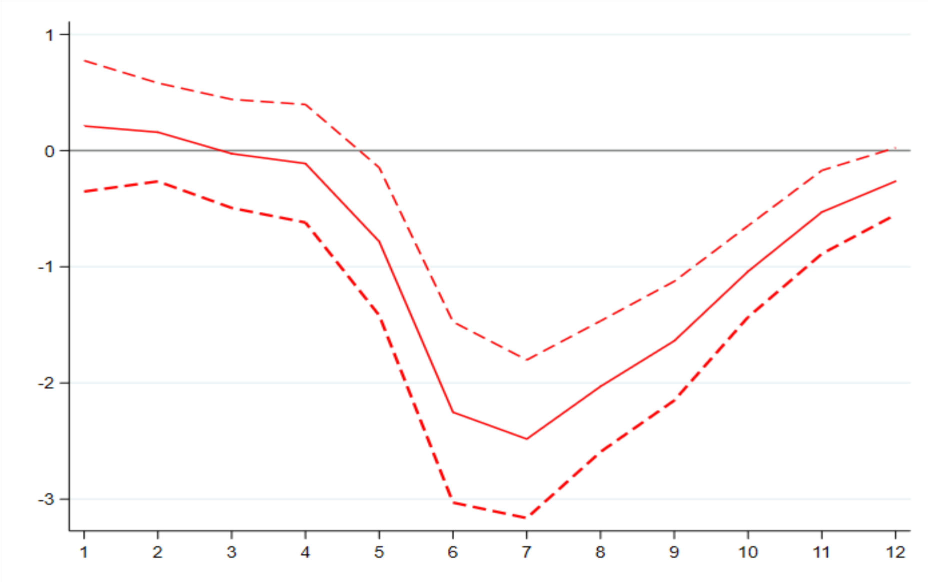
Table 1. Independent variables

	Mean	Std_dev	Median	10th Percentile	90th Percentile	N
Annual growth rate	0.0222	0.0345	0.0245	-0.0161	0.0593	1600
Inflation rate	3.5648	3.4251	2.6203	0.3639	8.5821	1600
Transformed FCI	0.0112	1.0379	-0.0132	-1.1748	1.3780	1600
Credit-to-GDP	1.3399	0.4144	1.2890	0.7665	1.8755	1600
Credit-to-GDP growth	0.0054	0.0107	0.0045	-0.0066	0.0183	1600
Credit boom dummy	0.0800	0.2714	0	0	0	1600

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 of real GDP growth

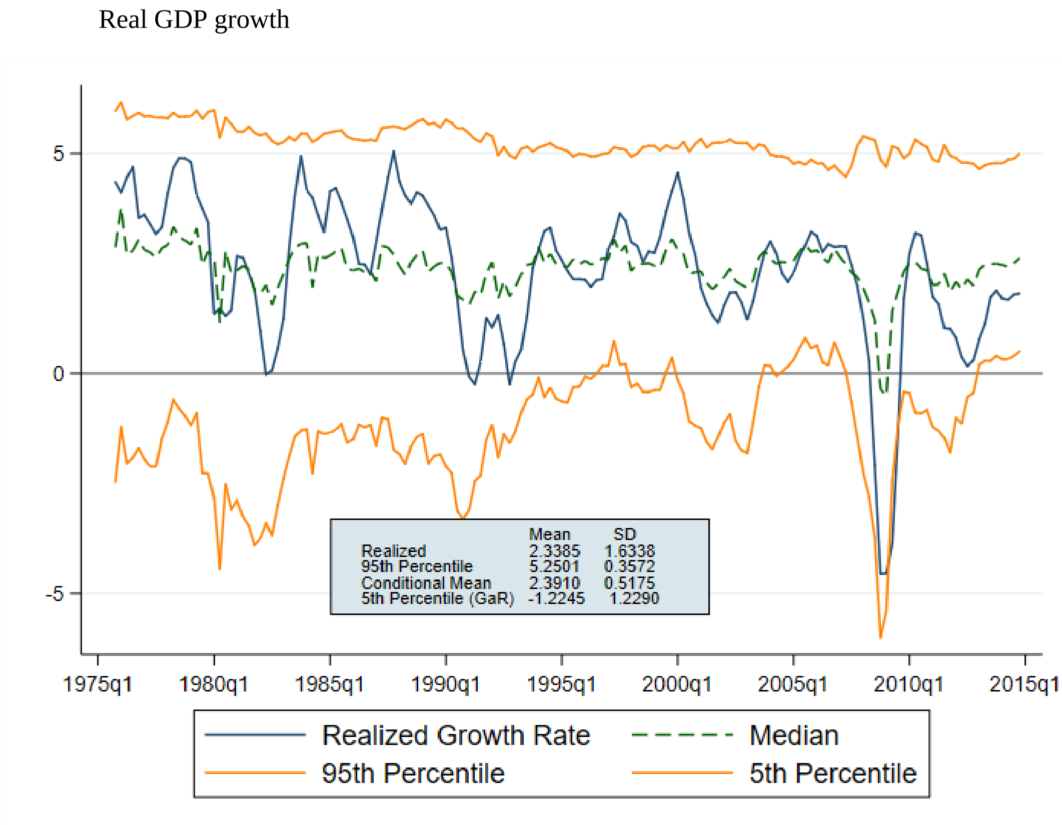
Real GDP growth



Quarters ahead

Note: Figure plots 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. Real GDP growth is measured in percent. 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. Predicted average conditional distribution of real GDP growth four-quarters ahead

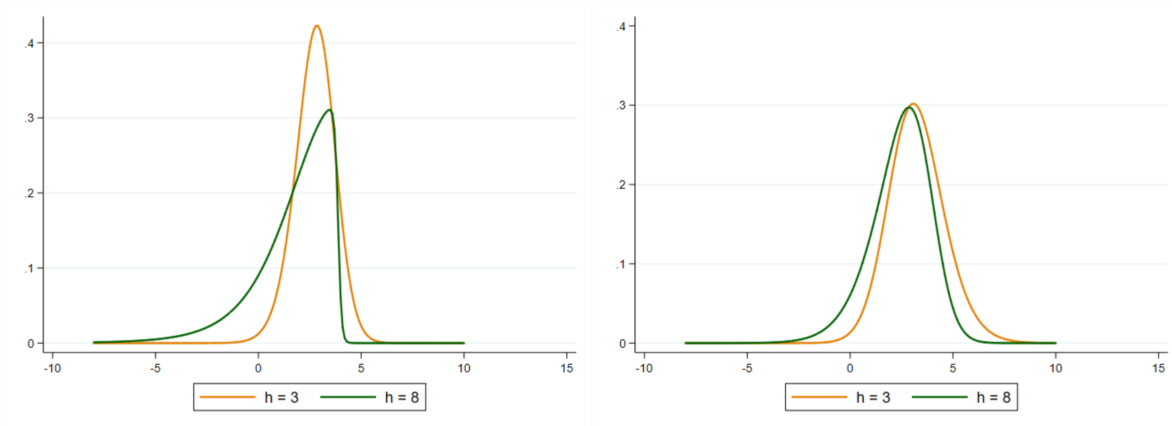


Note: Figure plots the cross-country averages of predicted conditional mean, 5th percentile (GaR), and 95th percentile of real GDP growth from estimation from panel quantile regressions. Real GDP growth is measured in percent. Advanced economies include 11 countries with data for most from 1973 to 2017

Figure 4. Probability density functions of conditional real GDP growth for three and eight quarters ahead

a. Loose FCI and credit boom

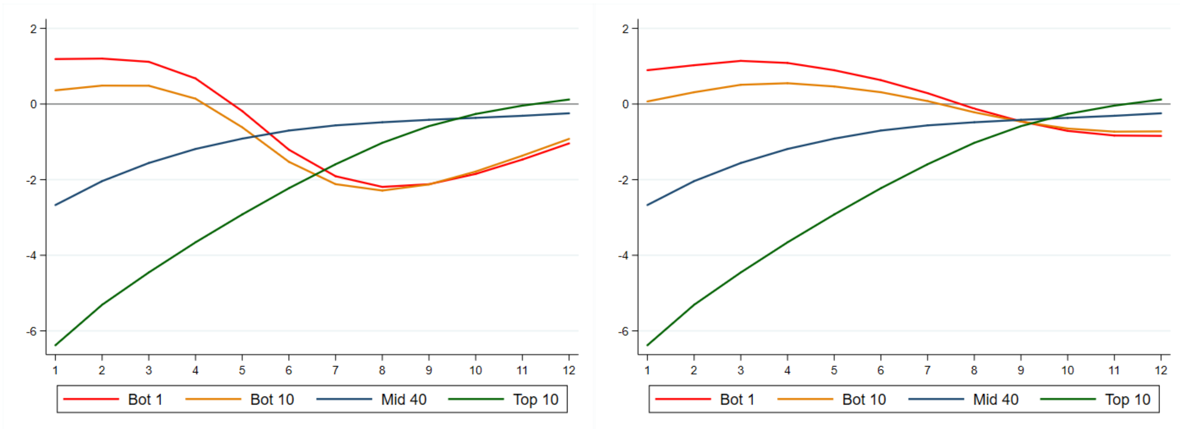
b. Loose FCI and no credit boom



Note: Probability density functions are estimated using panel quantile regression methods and fitted to a skewed t distribution and are shown for loose FCI (bottom 1 percent) by credit boom indicator for h equal to three and eight quarters. Real GDP growth, horizontal axis, is measured in percent. Advanced economies include 11 countries most with data from 1973 to 2017.

Figure 5. Term structures of GaR by FCI groups and credit boom indicator

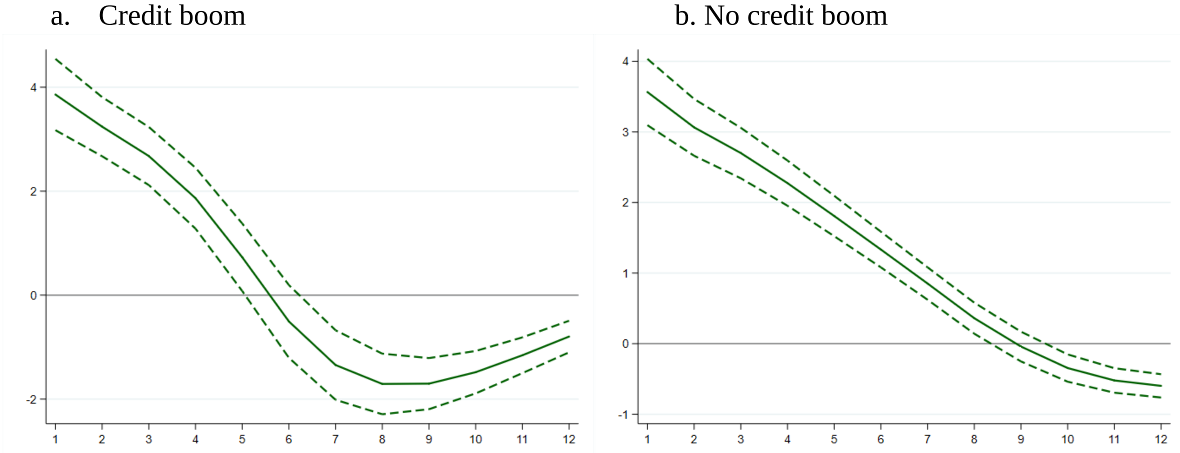
a. Credit boom　　　　　　　　　　　　b. No credit boom



Note: Figures plot the GaR (projected growth at the 5th percentile) at an annual rate. Real GDP growth, vertical axis, is measured in percent. The GaR projections are grouped on initial FCI levels for the bottom 1 percent, bottom decile, top decile, and Mid 40 (middle four deciles). Higher values of FCI represent tighter 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 of Loosest FCI minus average FCI groups, by credit boom indicator

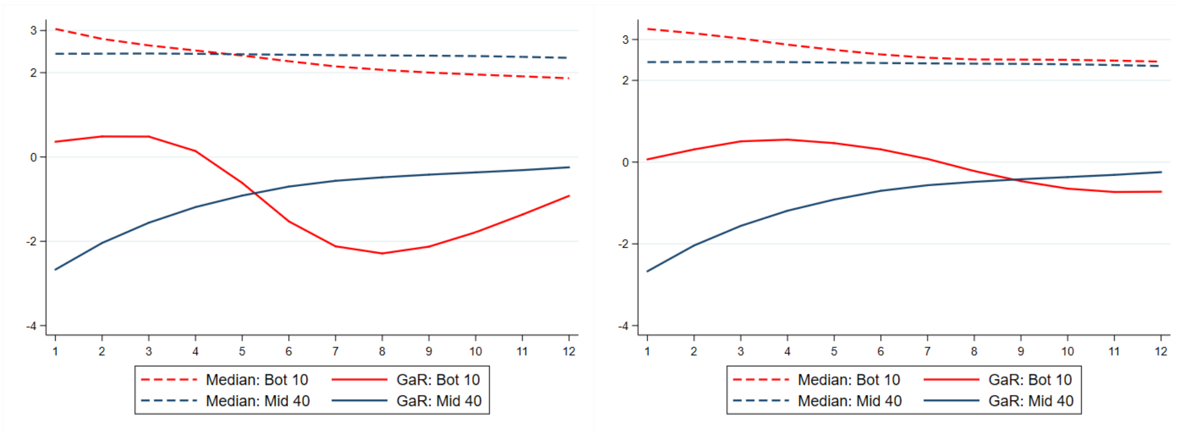
a. Credit boom　　　　　　　　　　　　b. No credit boom



Note: Figures plot the differences in the GaR term structures of the bottom 1 percent (Bot 1) minus the middle range (Mid 40) of FCI groups. Difference in real GDP growth, vertical axis, is measured in percent. 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 of predicted conditional median and GaR by initial FCI groups and credit boom indicator

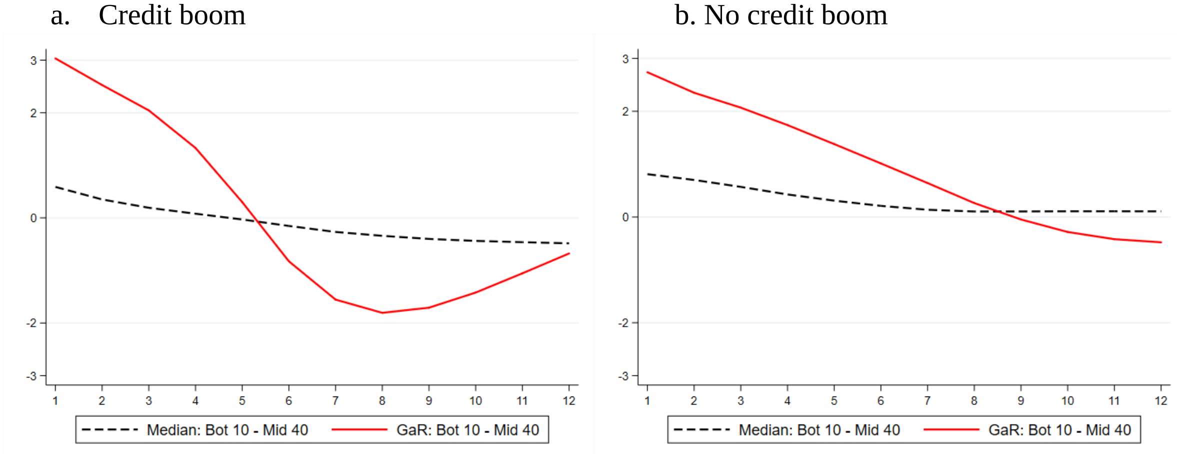
a. Credit boom b. No credit boom



Note: Figures plot projected median and GaR (projected growth at the 5th percentile) at an annual rate for initial FCI levels bottom decile (Bot 10) and middle range (Mid 40). Higher values of FCI represent tighter financial conditions. Real GDP growth, vertical axis, is measured in percent. 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 median and GaR term structures for Loose FCI minus average FCI groups, by credit boom indicator

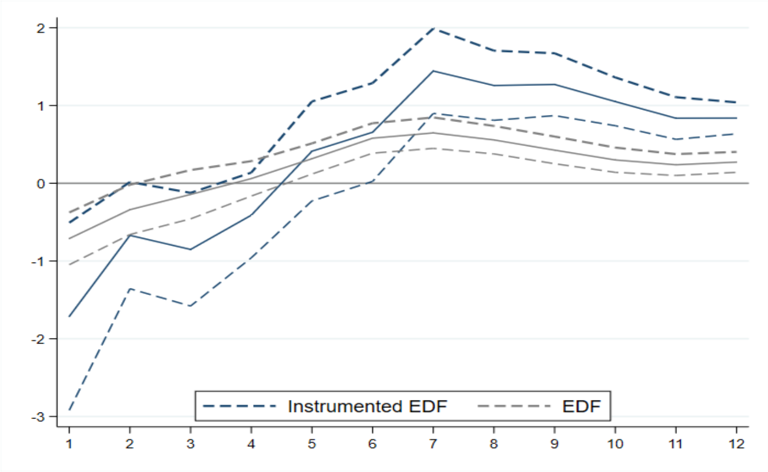
a. Credit boom b. No credit boom



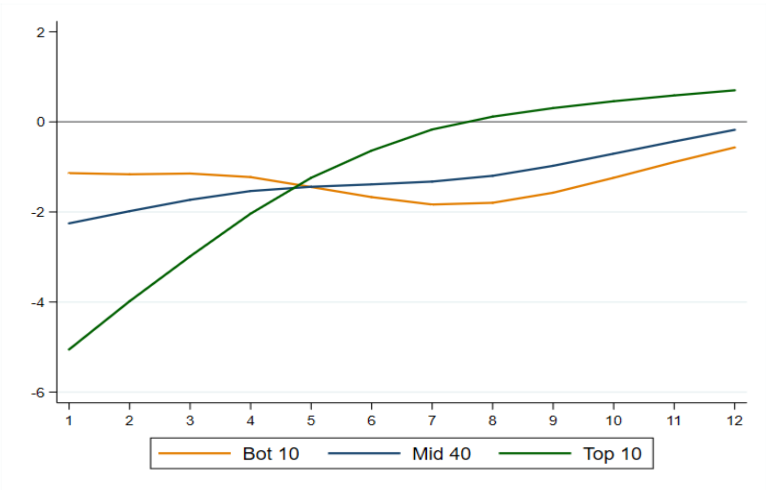
Note: Figures plot the differences in the projected median and GaR (projected growth at the 5th percentile) at an annual rate for initial FCI levels bottom decile (Bot 10) and middle range (Mid 40). Higher values of FCI represent tighter financial conditions. Difference in real GDP growth, vertical axis, is measured in percent. 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. Granular instrumental variables (GIV) for index of financial firm estimated default frequency (EDF) and the distribution of real GDP growth

a. Coefficients for financial firm EDF index and instrumented EDF index on the 5th percentile



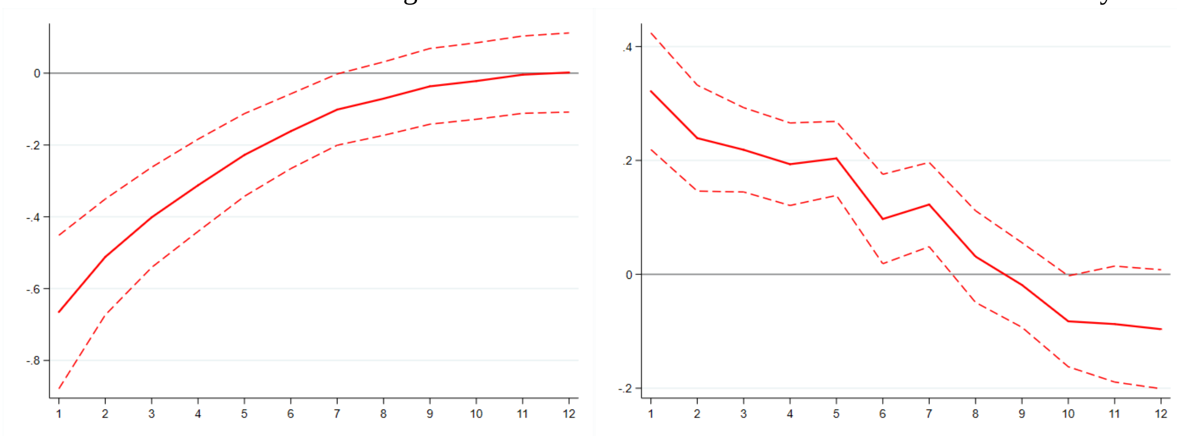
b. GaR term structures based on GIV of financial firm EDF index



Note. Panel a plots coefficient estimates on the financial firm EDF index and the GIV of the EDF index for the 5th percentile from quantile regressions using local projections based on nine AEs (sample excludes France and Spain because of too few observations to construct an instrument). The estimates are based on a shorter time period, starting in 1999:Q4 (rather than 1975 for most countries), than for FCI because EDFs are not available before then, and without a credit boom indicator given the short sample period. Panel b plots the term structure of GaR from estimations based on the GIV of the financial firm EDF index for initial EDF groups of the bottom 10 percent, middle four deciles, and top 10 percent, where higher EDF represents tighter financial conditions, from estimates for the shorter time period and without a credit boom indicator. Real GDP growth on the vertical axis is measured in percent.

Figure 10. Marginal effects of FCI on real GDP growth and volatility from two-step OLS estimations

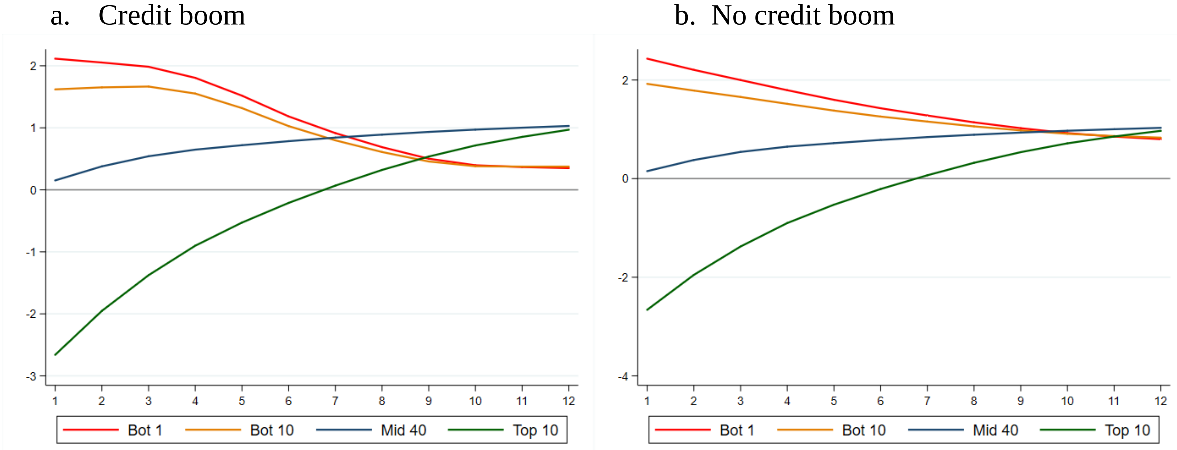
a. Coefficients on real GDP growth b. Coefficients on real GDP volatility



Note. Figures plot the estimated coefficients on the financial conditions index (FCI) on real GDP growth and volatility for projection horizons from one to twelve quarters. Higher FCI represents tighter financial conditions. Real GDP growth, vertical axis, is measured in percent. 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 11. Term structures of GaR by initial FCI groups and credit boom indicators from two-step OLS estimations

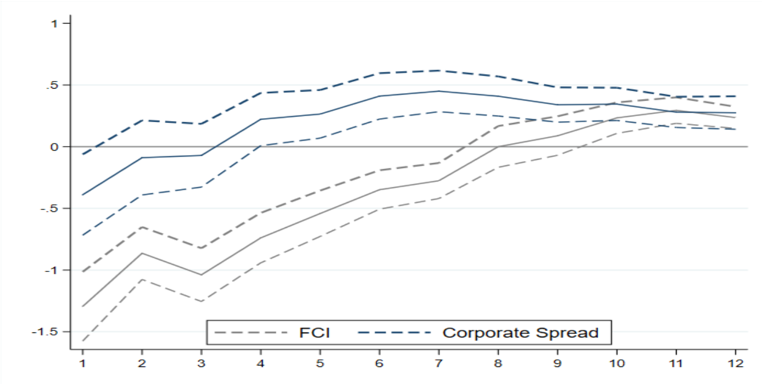
a. Credit boom b. No credit boom



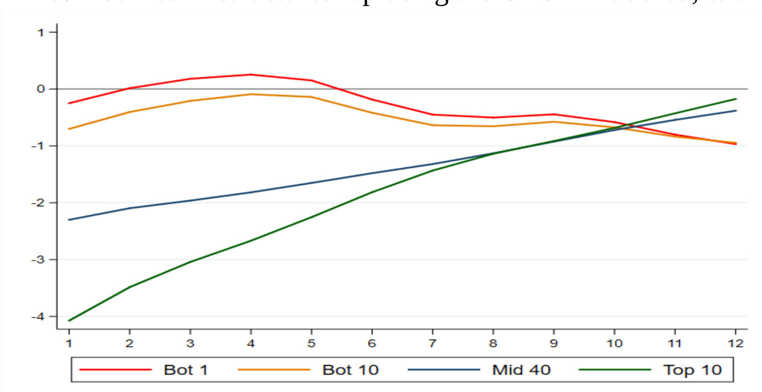
Note: Figures plot the projected GaR (growth at the 5^{th} percentile), at an annual rate, based on estimates of the mean and volatility of growth. The GaR term structures are shown for initial FCI groups for the bottom 1 percent, bottom decile, top decile, and a middle range. Higher values of FCI represent tighter financial conditions. Real GDP growth, vertical axis, is measured in percent. 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 12. Robustness analysis of corporate bond spreads and the Global Financial Crisis (GFC)

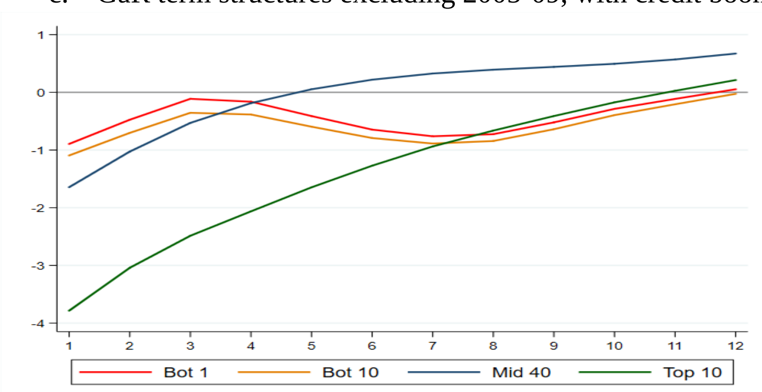
a. Corporate bond spread and FCI coefficients for 5th percentile of real GDP growth



b. GaR term structures replacing the GFC in 2008-09, with credit boom



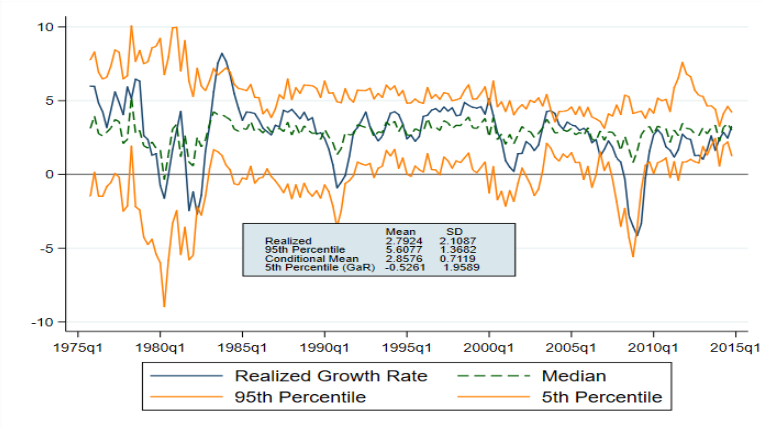
c. GaR term structures excluding 2005-09, with credit boom alternative



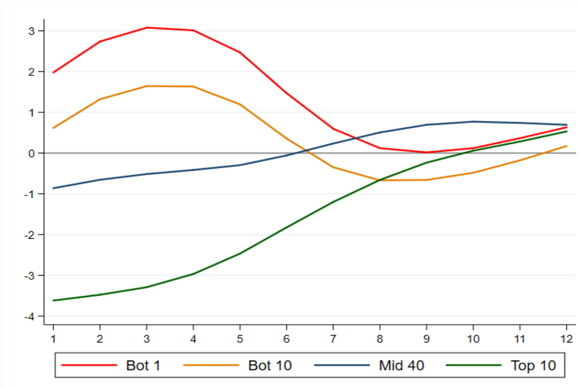
Note: Panel a plots the coefficients on corporate bond spreads for the 5th percentile and median where spreads replace the FCI in equation 1, and similar coefficients on FCI in equation 1. Panel b plots the GaR term structures excluding the GFC by replacing 2008-09 with with average values of 2007 and 2010. Panel c plots the GaR term structures excluding 2005 to 2009, and defining credit boom by the interaction of loosest two deciles of FCI and fastest two deciles of nonfinanical credit-to-GDP growth. The GaR estimates are grouped on initial FCI levels of the bottom 1 percent, bottom decile, top decile, and a middle range (Mid 40). 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. Real GDP growth, vertical axis, is measured in percent.

Figure 13. Estimates for USA only

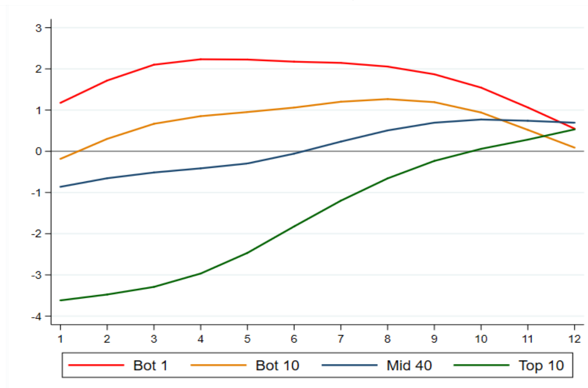
a. Predicted distribution of real GDP growth for four quarters ahead, USA



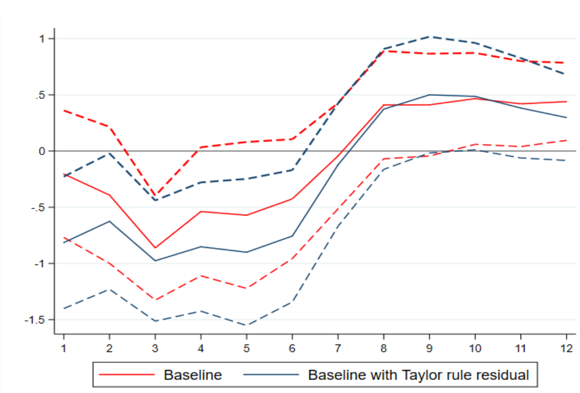
b. GaR term structures, credit boom



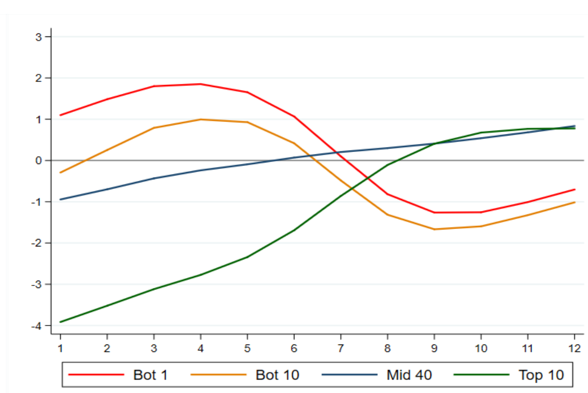
c. GaR term structures, no credit boom



d. FCI coefficients on 5th percentile



e. GaR term structure, Taylor rule residual



Note: Panel a plots the time series of the expected growth distribution from quantile regressions for the USA only and panels b anc c plots the GaR term structures for the USA only. Panel d plots coefficient estimates on FCI adjusted for monetary policy following the model in equations (6) and (7) from quantile regressions for the US only, for models with and without Taylor rule residuals. Estimates are based on quantile regressions with local projection estimation methods, and standard errors are from bootstrapping techniques. Panel e plots the GaR term structures for the model with Taylor rule residuals. Real GDP growth, vertical axis, is measured in percent.

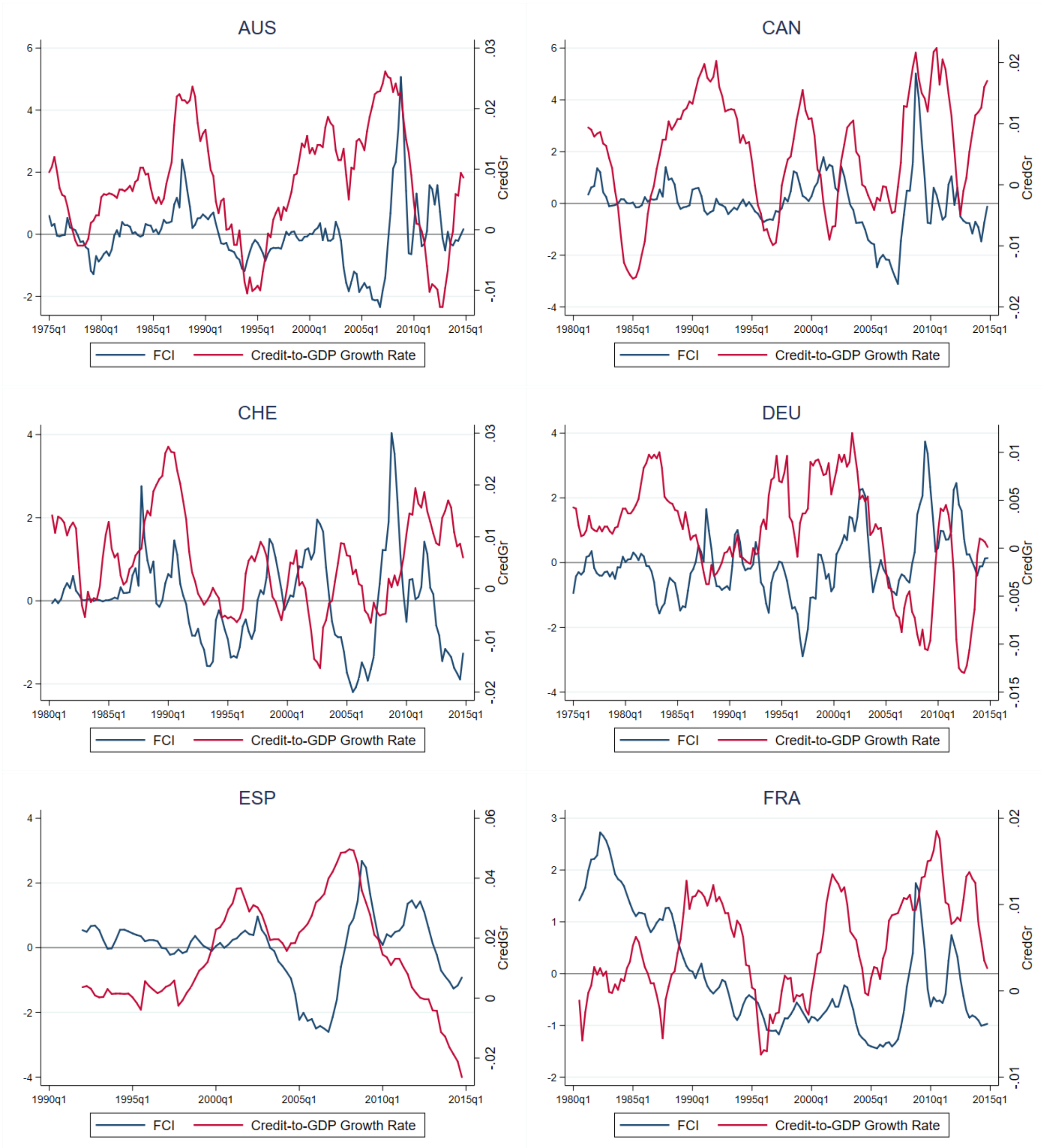
Appendix A. Start dates for model estimation and for individual components of FCI

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




GBR
ITA
JPN
SWE
USA
FCI
Credit-to-GDP Growth Rate
CredGr
1975q1
1980q1
1985q1
1990q1
1995q1
2000q1
2005q1
2010q1
2015q1

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