Targeted Financial Conditions Indices and Growth-at-Risk*

Fernando Eguren-Martin[1], Sevim Kösem[2], Guido Maia[3], and Andrej Sokol[4]

[1]SPX Capital
[2]The American College of Greece
[3]Autonomy Capital
[4]Bloomberg LP

May 15, 2026

Abstract

We propose a novel approach to extract factors from large data sets that maximize covariation with the quantiles of a target distribution of interest. As an application, we build targeted financial conditions indices for the quantiles of future US GDP growth. We show that our indices yield considerably better out-of-sample density forecasts than competing models, as well as insights on the importance of individual financial series for different quantiles of GDP. Notably, leverage indicators appear to co-move more with the median of the predictive distribution, while credit and risk indicators are more informative about downside risks.

Keywords: Quantile regression, factor analysis, financial conditions indices, GDP-at-risk.

JEL Codes: C32, C38, C53, C58, E37, E44.

---

*Disclaimer: the views expressed in this paper are those of the authors, and do not necessarily reflect those of Bloomberg LP, Autonomy Capital or SPX Capital. We are grateful to Scott Brave, Max Doví, Ana Galvao, Domenico Giannone, Scott Johnson and seminar participants at Deutsche Bundesbank, National Bank of Belgium, SOFiE Annual Meeting 2024 and IAAE Annual Conference 2025 for helpful comments.
Conflict of interest statement: the authors have no conflict of interest to declare.
Corresponding author: Andrej Sokol, asokol14@bloomberg.net.

1 Introduction

The importance of the financial system in both pricing and influencing macroeconomic developments is widely recognized. One expression of that is the widespread use of financial variables for macroeconomic modelling, both theoretical and empirical (see Bernanke et al., 1999, Gertler and Kiyotaki, 2010, Christiano et al., 2014 and Gilchrist and Zakrajsek, 2012, among many others). A frequent challenge is the wide range of candidate variables for such modeling efforts. The development of so-called financial conditions indices (FCIs), which summarise information contained in a large number of variables, is a response to that problem (see Arrigoni et al., 2022, for a recent review and assessment). FCIs have been monitored in their own right, but also used for forecasting and other analytical purposes. Among these, "at-risk" modelling, which seeks to explain the occurrence and assess the likelihood of tail events for a range of variables, has emerged as a very popular application, starting with Adrian et al. (2019).

The standard approach for modelling such outcomes typically entails using a pre-existing measure of financial conditions, usually designed with the sole aim of capturing common variation across a wide range of financial variables.[1] However, that may lead to a disconnect between the way financial conditions indices are constructed and their subsequent use. Starting from this observation, we propose a method to extract financial conditions indices that are specifically tailored to explain or forecast any part of the distribution of a variable of interest. That is, we devise a methodology to estimate *targeted* financial conditions indices (TFCIs), notably for "at-risk" modelling applications.

Our approach works by rotating an initial orthogonalization of a panel of variables – in our case, the components of the Chicago Fed's National Financial Conditions Index (NFCI, Brave and Butters, 2011) – in order for one or more of the resulting components to maximize covariation with individual quantiles of a target of interest – in our application, future US GDP growth. We show that this approach yields indices that are economically intuitive, smoother when computed in real time, and with better out-of-sample forecasting power than existing alternatives.

[1] With the notable exception of Giglio et al. (2016), which we discuss in detail below.

Specifically, We show that our model delivers statistically and economically significant gains in terms of probability scores and better-calibrated densities than a number of alternatives, including the NFCI itself. Moreover, we also find that compared to a more "traditional" index based on principal component analysis (PCA), a TFCI optimised to forecast the left tail of GDP growth one year ahead tends to put more emphasis on developments in credit and risk rather than leverage. The opposite is true for a TFCI for the conditional median.

Related literature. Our paper is related to several literature strands. Most directly, it complements papers that develop financial conditions indices (Hatzius et al., 2010, Brave and Butters, 2012, Kremer et al., 2012, Arregui et al., 2018 and Arrigoni et al., 2022), and those that make use of such indices to model tail risk in macroeconomic and financial variables (Adrian et al., 2019, Adams et al., 2021, Chari et al., 2020, Figueres and Jarociński, 2020, Eguren-Martin et al., 2021, Eguren-Martin and Sokol, 2022, Gelos et al., 2022, Amburgey and McCracken, 2023, among others). By performing both steps jointly, our paper seeks to link the two. More broadly, the paper offers a novel approach to handling "big data" for risk modeling purposes; as such, it also relates to papers such as Plagborg-Møller et al. (2020) and Chi et al. (2025).

Many of the "at-risk" papers cited above, as well as our own approach, also fit the factor-augmented quantile regression framework of Ando and Tsay (2011). But while the focus of that paper was on developing methods for selecting the optimal number of principal components of a data set to include in a model, we go one step further by allowing for targeted factor extraction based on a variable of interest.

Giglio et al. (2016) propose an approach, called partial quantile regression in analogy to partial least squares, which seeks to summarize the cross section of a set of predictors according to their covariation with a given quantile of a target variable. But one reason to develop our own approach is that with a large panel such as the one underlying the NFCI, we have found their method to be wanting in terms of out-of-sample performance.[2] We conjecture that this is due to the ability of our approach to remove some idiosyncratic variation from the financial series before

[2] Giglio et al. (2016) illustrate their approach on a panel of 19 variables, roughly a fifth of the size of our panel.

focusing on fitting the quantiles of the target variable.

Finally, it is worth distinguishing our approach from so-called "quantile factor models" (Ando and Bai, 2020, Chen et al., 2021). The aim of those approaches is to uncover factors driving quantile covariation across a panel of variables. While our TFCIs can sometimes exhibit meaningful covariation with some of the quantiles of the underlying financial series – for example, tail outcomes in credit spreads coinciding with spikes in the TFCI – that relationship is entirely subordinate to the aim of delivering covariation between the TFCI and a specific quantile of the target variable.

Paper structure. The rest of the paper is organized as follows: in Section 2 we introduce our approach to targeted factor extraction. In Section 3 we apply our method to US financial conditions and GDP growth and revisit the drivers underlying growth-at-risk. In Section 4 we compare out-of-sample performance to available alternatives, and in 5 we conclude.

2 *Targeted* Factor Extraction

In this section we outline our novel approach to factor extraction, the main contribution of our paper. Our objective is to extract one or more common factors from a potentially very large set of variables. The crucial restriction is that the factors are required to maximize the forecasting power of our model for a specific quantile and horizon of a target variable. In our application, the set of variables from which factors are extracted are the series underlying the Chicago Fed's National Financial Conditions Index (NFCI), and the target variable is US GDP growth at different horizons.

In a nutshell, our approach uses orthonormal rotations to re-orient an initial factor decomposition of the underlying (financial) variables so as to maximize their explanatory power for a given quantile and horizon of our target variable (GDP growth). Let z_t be an observation from a panel of n series that have mean zero and (for simplicity) unit variance. Let $\mathbb{Z}$ stack the T observations z_t', and $\mathbb{F}$, which stacks f_t', be any factor decomposition of $\mathbb{Z}$, for example the full set of (standardised) PCA scores. Then

$$z_t = \Lambda f_t \tag{1}$$

where Λ is a $n \times n$ matrix of factor loadings. Any orthonormal rotation of Λ and $\mathbb{F}$ will also yield an admissible factor decomposition of $\mathbb{Z}$. Thus, let $G(\theta)$ be a $n \times n$ rotation matrix parametrised by the vector of angles θ. A set of new factors $\tilde{f}_t(\theta)$ can be recovered by simply rotating the original factors (or equivalently, loadings), because

$$z_t = \Lambda f_t = \Lambda G(\theta) G'(\theta) f_t \equiv \tilde{\Lambda}(\theta) \tilde{f}_t(\theta) \tag{2}$$

$G(\theta)$ is constructed in a similar fashion as in Haberis and Sokol (2014), namely as the product of suitably chosen Givens matrices:

$$G(\theta) = \prod_{i=1}^{\min(s,n-1)} \prod_{j=i+1}^{r} G_{i,j}(\theta_{i,j}) \tag{3}$$

where the only non-zero elements of $G_{i,j}(\theta_{i,j})$ are $g_{kk} = 1$, $k \neq i, j$; $g_{kk} = \cos\theta_{i,j}$, $k = i, j$ and $g_{ji} = -g_{ij} = -\sin\theta_{i,j}$. The parameter $r \leq n$ determines the dimension of the column (sub-) space of Λ that is rotated by $G(\theta)$, while $s < r$ controls the number of factors included in the regression models (see below). As further discussed in Section 3, we choose r, the dimension of the column space to be rotated, dynamically for each vintage, quantile and horizon from a grid, based on local fit adjusted for degrees of freedom $(R^1(\tau))$, defined as

$$R^1(\tau) = 1 - \frac{\hat{V}(\tau)}{\tilde{V}(\tau)} \frac{T-1}{T-p} \tag{4}$$

where $\hat{V}(\tau)$ denotes the sum of weighted absolute residuals of a candidate model, $\tilde{V}(\tau)$ the sum of weighted absolute residuals of a model consisting only of a constant and p is the total number of parameters, including the angles in θ.[3]

Consider the following specification of the conditional quantile function of response

[3]Since $\hat{V}(\tau)$ is also the key ingredient of the likelihood of a linear quantile regression model, this is essentially a shortcut to the likelihood ratio test proposed by Koenker and Machado (1999), the only difference being the absence of an adjustment for curvature.

variable y_{t+h} for quantile τ:

$$\begin{aligned}
Q\left(y_{t+h}|w_t,\ \tilde{f}_t\left(\theta_\tau\right),\tau\right) &= \alpha(\theta_\tau)'w_t + \gamma_\tau'\left(\theta_\tau\right)s_\tau\tilde{f}_t\left(\theta_\tau\right) \\
&= \left[\begin{array}{cc} \alpha(\theta_\tau)' & \gamma_\tau'\left(\theta_\tau\right)\end{array}\right]\left[\begin{array}{c} w_t \\ s_\tau\tilde{f}_t\left(\theta_\tau\right)\end{array}\right] \\
&\equiv \beta_\tau'\left(\theta_\tau\right)x_t\left(\theta_\tau\right) \qquad (5)
\end{aligned}$$

Here w_t captures any explanatory variables not included in z_t, such as deterministic terms or lagged values of y_t, and s_τ is an $s \times n$ matrix that selects the first $s \leq n$ elements of $\tilde{f}_t\left(\theta_\tau\right)$; the parameter s controls the number of factors included in the regression and determines the length of $\gamma_\tau\left(\theta_\tau\right)$. We limit ourselves to $s = 1$; that is, we stick to a single factor to be used for the modeling of our variable of interest. This is motivated by the objective to have a single financial conditions index, both for ease of tracking its time variation and for comparison with existing methods.[4]

For a given rotation of the original factors by a set of angles θ_τ, $\hat{\beta}_\tau\left(\theta_\tau\right)$ solves the linear quantile regression problem

$$\hat{\beta}_\tau\left(\theta_\tau\right) = \arg\min_{\beta_\tau(\theta_\tau)} \frac{1}{T}\sum_{t=1}^{T}\rho_\tau\left(y_t - \beta_\tau'\left(\theta_\tau\right)x_t\left(\theta_\tau\right)\right) \qquad (6)$$

where $\rho_\tau\left(u\right) = u\left(\tau - \mathbb{I}\left(u < 0\right)\right)$ is the check function.

Our object of interest is θ_τ^*, the set of angles, and therefore rotated factors that, given a choice of r and s, maximizes the fit of the model:

$$\theta_\tau^* = \arg\min_{\theta_\tau} \frac{1}{T}\sum_{t=1}^{T}\rho_\tau\left(y_t - \hat{\beta}_\tau'\left(\theta_\tau\right)x_t\left(\theta_\tau\right)\right) \qquad (7)$$

θ_τ^* is not available in closed form, but can be recovered by numerical optimization.

[4] Ando and Tsay (2011) investigate the choice of s in the context of choosing the optimal number of *PCA* scores to include in a factor-augmented quantile regression. Their methods are not directly portable to our setting, while our approach for choosing r based on R^1, or the likelihood ratio test in Koenker and Machado (1999) can be easily extended to the choice of s. However, to avoid over-fitting, $s << r$, that is, only a small subset of the rotated factors will enter the regression.

To summarize, in our application, we have, for each horizon and quantile of interest, a fitted model of the following form:

$$\hat{Q}\left(\Delta gdp_{t+h,t}|x_t\left(\theta^*_\tau\right),\tau\right) = \beta'_{\tau,h}\left(\theta^*_{\tau,h}\right)\begin{bmatrix} 1 \\ \Delta gdp_{t,t-h} \\ \tilde{f}_t\left(\theta^*_{\tau,h}\right)\end{bmatrix} \tag{8}$$

where $\Delta gdp_{t+h}, t$ denotes GDP growth between periods t and $t+h$, 1 multiplies a (quantile- and horizon-specific) constant and $\tilde{f}_t\left(\theta^*_{\tau,h}\right)$ is our targeted factor, which is also quantile- and horizon-specific.

3 Targeted Financial Conditions Indices and US Growth-at-Risk

To showcase the main advantages of our approach, we model the predictive distribution of US GDP growth, the chosen target variable of several recent contributions to the "at-risk" literature (Giglio et al., 2016, Adrian et al., 2019, Adams et al., 2021, Plagborg-Møller et al., 2020, among others). We first describe the construction of our targeted financial conditions indices and then discuss their main features and differences with respect to other approaches.

3.1 Data and Index Construction

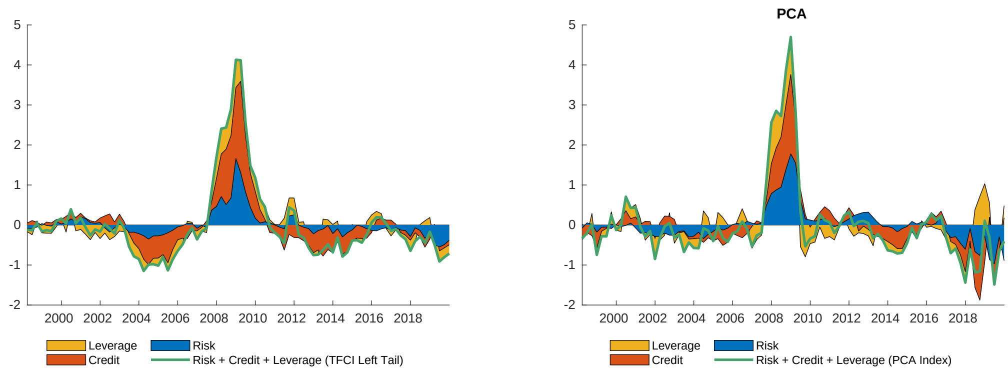
There is a tradition of papers extracting information from financial variables for monitoring and forecasting purposes (see Section 1). Due to its popularity, we take the Chicago Fed's NFCI (Brave and Butters, 2011) as our starting point.

Specifically, we focus on the more than 100 series comprising the NFCI, at monthly frequency and over the 1973-2019 sample.[5] The authors group these series into three categories: leverage, credit and risk; we follow that categorization in our color-coding in subsequent charts.[6] We start by standardising the underlying con-

[5] The data are available on the Chicago Fed website here.

[6] See Table A.1 for a full list of the series included. Although some series already start in 1971, we follow Brave and Butters (2011) in considering data form 1973 onwards, which is when

Figure 1 Left tail TFCI and PCA index - 1 Year Ahead



(a) TFCI left tail index

(b) PCA index

Note: Ex-ante time series of the a) Left Tail TFCI (5th Percentile) and b) PCA Index, when forecasting 1 year ahead. Contributions from leverage (yellow), credit (red) and risk (blue) are also shown. Both indices have been standardized.

tributions (as only these, rather than the raw underlying series, are available) to then extract principal components, which we use both as a benchmark and as the starting orthogonalization for our method (see Section 2).[7]

We focus on a range of quantiles of GDP growth, both 1 and 4 quarters ahead, in line with the literature.[8] For each horizon, the specification of our model is as laid out in equation (8). Given our focus on delivering a single targeted financial conditions index for each quantile and horizon, we use a single factor for our forecasts (that is, we set $s_\tau = 1$ for any quantile τ). Moreover, we choose r (which determines the number of standardized PCA scores to be rotated) from a dynamic grid capped at 15% of the number of available indicators in each vintage, in order to avoid overfitting.[9]

at least 25% of the series comprising the final dataset become available.

[7] While the NFCI is based on a dynamic factor model, the correlation between the extracted factor and the first principal component of the underlying data is 0.97 over our forecast evaluation sample (see next Section).

[8] 1 quarter ahead, the left-hand side variable is the seasonally-adjusted quarter-on-quarter annualized growth rate; 1 year ahead, it is the year-on-year growth rate.

[9] We conjecture that our ability to set the parameter r is one reason for the better out-of-sample performance of our approach compared to Giglio et al. (2016), as setting $r << n$ allows to filter out some idiosyncratic variation from the financial variables before focusing on covariation with individual quantiles of our target.

3.2 Financial Conditions and US GDP-at-Risk Over Time

We focus on the 5^{th} percentile of the distribution of US GDP growth 4 quarters ahead, one working definition of growth-at-risk (see, for example, IMF, 2017). The left panel of Figure 1 shows the ex-ante[10] evolution of the TFCI that results from targeting the 5^{th} percentile of GDP growth 4 quarters ahead, decomposed into the contributions of each category. The right panel shows an analogous plot for a PCA-based version, where the index in each period is the last observation of the first principal component of the underlying series available at the time.[11] Higher values indicate tighter financial conditions. We show the PCA-based version as a benchmark for two reasons. First, over the sample shown in Figure 1, the first principal component of our most recent data vintage (2019Q4) correlates almost perfectly with the corresponding NFCI vintage. And second, PCA scores are the starting point of our approach, so differences in loadings between our index and the first principal component are an object of interest in its own right.

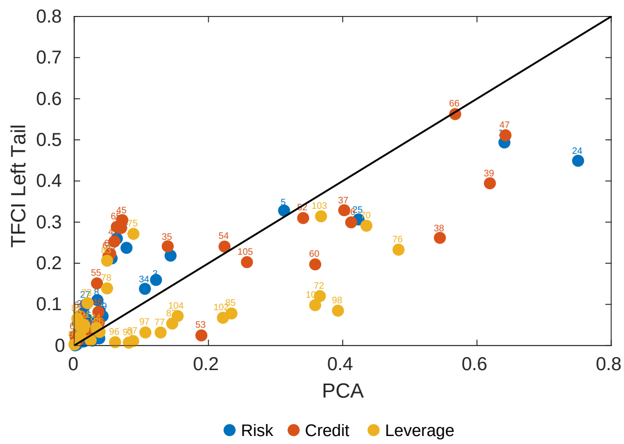
There are a few points worth highlighting. First, and most notably, both indices increase sharply as the global financial crisis (GFC) starts unfolding in 2007, with similar dynamics and relative contributions from the three groups of variables. However, apart from that period, the two indices exhibit more heterogeneous behaviour: our index is smoother, with contributions from each variable category building up and retracing over time. In contrast, the PCA-based version is significantly more volatile, both in terms of the aggregate index and the contributions of the various groups. Another feature that stands out is that in the run-up to the GFC, our TFCI for the left tail pointed to a more protracted period of loose financial conditions.

Our framework also offers insights into which financial variables are associated most strongly with the dynamics of a quantile of interest. While this of course does not imply causation, it is nevertheless suggestive and can be associated to

[10] So for each period, it shows the last observation of the TFCI obtained from the standardizesd and orthogonalized financial series, available up to T_v and rotated by $\theta^*_{\tau,h}$. That's in contrast to the ex-post series resulting from the estimation step, which is only available up to $T_v - h$.

[11] In both cases, the contributions to the indices in each period are obtained by inverting $\tilde{\Lambda}\left(\theta^*_{\tau,h}\right)$ and multiplying the elements of the first row by the original (standardized) underlying series.

Figure 2 Average Ex-Ante Squared Loadings, 1 Year Ahead



Note: Sample averages of ex ante squared loadings for the PCA vs. Left Tail TFCI indices, when forecasting 1 year ahead. Each dot corresponds to one component series. See Table A.1 for the series' legends.

existing narratives about the links between the financial sector and the macro economy. Figure 2 thus compares the squared loadings of the components of our TFCI with the loadings on the first principal component, both averaged across all vintages in our sample.[12] Each dot corresponds to one of the component series, colour-coded according to the three broad groups they belong to.[13] Series close to the diagonal behave similarly in the TFCI and a in PCA-based index, while series above it tend to comove more closely with our TFCI than with the first principal component score.

Two features of Figure 2 stand out. First, our index is not as tightly linked to the movements of a few variables as PCA is. This can be inferred from the fact that most of the series with squared loadings above 0.3 lie below the 45-degree line. Second, compared to PCA, our index appears to co-move less strongly with indicators of leverage, and more strongly with credit and risk indicators, corroborating

[12]In each vintage, squared loadings correspond to the share of variance of each indicator explained by the factor/index in question.

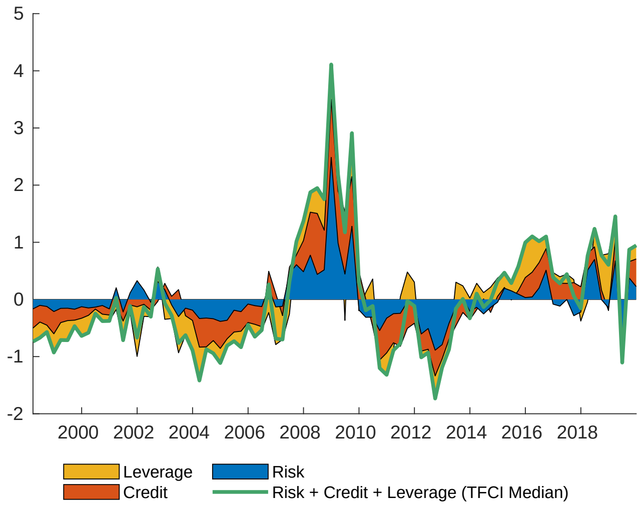
[13]Table A.1 in the Online Appendix provides a full legend.

earlier findings on the role of credit for predicting crisis-type events (Schularick and Taylor, 2012). That said, the variables displaying the highest squared loadings are similar across approaches: some credit-related variables, mostly survey-based measures of access to credit for consumers and small firms (from National Federation of Independent Business (NFBI) Small Business Economic Trends (SBET) and Federal Reserve Board (FRB) Senior Loan Officer surveys), and a few risk-related ones, such as the slope of the US Treasury yield curve and interbank deposit spreads.

Finally, Figure 3 shows a version of our TFCI that targets the median of the distribution of US GDP growth one year ahead, rather than its left tail. Compared to the one targeting the 5^{th} percentile (shown in Figure 1), this index captures broad cyclical conditions and displays more even contributions from the three types of components. This is also evident from the squared loadings of each series on the median-based TFCI compared with its left-tail counterpart (Figure A.3 in the Appendix). The former explains a higher share of the variance of several indicators of leverage, and a lower share of the variance of a number of credit indicators. The stronger correlation of leverage-type variables with indices that target business cycle-type variation can also be understood in terms of earlier findings, notably related to the relevance of financial accelerator-type dynamics in explaining economic activity (see Bernanke et al., 1999, among many others).

In sum, financial conditions indices based on common variation across financial variables (such as PCA) tend to tightly comove with a relatively small number of indicators, and that this is no longer the case with factors extracted using our approach. Moreover, our TFCIs for the left tail and median of future GDP growth, suggest that different types of financial variables contain relevant information for each. Leverage-type variables appear to be more important for forecasting the center of the predictive distribution, while risk and credit variables are more important for forecasting left-tail events. After reviewing this qualitative evidence, we turn next to the out-of-sample forecasting performance of our TFCIs.

Figure 3 Median TFCI and contributions - 1 Year Ahead



Note: The figure plots the ex-ante (standardized) Median TFCI when forecasting 1 year ahead. Contributions from leverage (yellow), credit (red) and risk (blue) are also shown.

4 Out-of-Sample Performance

We evaluate the out-of-sample forecasting performance of our approach for US GDP growth, considering 1- and 4-quarters-ahead forecasts. We compare it to three alternatives: a model that relies on the Chicago Fed's NFCI, used in the pioneering "at-risk" literature (among others Adrian et al. (2019) and Adams et al. (2021)); an even simpler variant that uses the first principal component (PCA) of the series underlying the NFCI; and a model that uses quantile-specific indices constructed with Giglio et al. (2016)'s partial quantile regression method (GKP). In all cases, we include lagged GDP growth as an additional regressor, as well as a constant. Overall, we find that our model performs considerably better than the alternatives across the entire predictive distribution on a number of established metrics.

Our evaluation sample spans 1999Q1:2019Q4, and therefore includes both the early 2000s recession and the GFC.[14] To avoid look-ahead bias in the construction of the

[14]Results extending our sample to the pandemic period are shown in the Online Appendix, Figures A.7 and A.8.

indices, we compute our TFCI, as well as the PCA and GKP indices recursively from the underlying financial data, using only information that was available in real time. This also means fewer financial variables enter the indices in earlier samples than in later ones.[15] For the NFCI, we use the 2019Q4 vintage up to the forecast date in each vintage; in principle, this benchmark therefore suffers from look-ahead bias and should have an advantage relative to the other models. However, that is not borne out in our results, and even using real-time NFCI vintages (Amburgey and McCracken, 2023) does not change the overall picture.[16] Finally, as in Adams et al. (2021), we abstract from the issue of GDP revisions and simply use the 2019Q4 vintage consistently across models.

We focus on two main evaluation metrics: quantile scores, and a set of quantile-weighted scores proposed by Gneiting and Ranjan (2011). In the Online Appendix, we also compare calibration by means of probability integral transforms (PITs).[17]

The quantile score (or tick loss function, see Giacomini and Komunjer, 2005) for each data vintage v is defined as

$$QS_{v,\tau,h} = \rho_\tau \left(y_{t_v+h} - \hat{P}^{-1}_{v,h}(\tau) \right) \tag{9}$$

The score penalises outturns that are more extreme (i.e. fall further in the corresponding tail) than the predictive quantile $\hat{P}^{-1}_{v,h}(\tau)$. It stands in the same relation to the loss function used in quantile regression (Koenker and Bassett, 1978) as the squared forecast error to OLS regression.

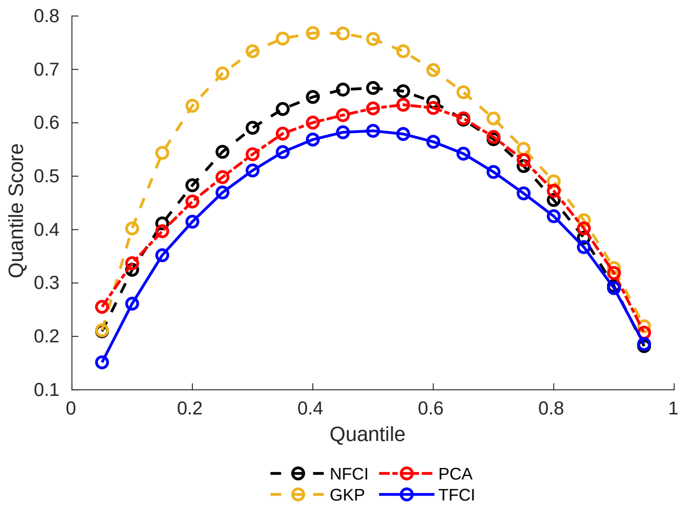
We follow Gneiting and Ranjan (2011) and plot average quantile scores for all models over our evaluation sample in Figure 4 for 4-quarter-ahead projections (see Figure A.4 in the Appendix for 1-quarter ahead projections). For both the 1-quarter- and 4-quarters-ahead horizon, our model forecasts yield average quantile scores lower or equal to those from all other models across quantiles. This

[15] For each vintage, we keep only variables that were available for at least 50% of the sample up until the forecast date. This avoids distortions by ensuring that only indicators with sufficient variation over the estimation sample are considered in each vintage.

[16] See Online Appendix, Figure A.6.

[17] Figures A.1 and A.2 in the Online Appendix show data outturns against estimated predictive densities for all models.

Figure 4 Average Quantile Scores



Note: Average quantile scores, 1 year ahead. Lower values indicate better performance.

indicates that our method is competitive across the entire distribution, and that the summary scores discussed next are not driven by its performance in a specific region.

Gneiting and Ranjan (2011) also propose a set of quantile-weighted versions of continuously ranked probability scores to assess forecasting performance in specific regions of the predictive distribution. The general form of their scores is

$$GR_{v,\tau,h} = \int_0^1 QS_{v,\tau,h} w\left(\tau\right) d\tau \tag{10}$$

where w are non-negative weight functions on the real line. GR scores are essentially variously-weighted sums of the quantiles scores discussed above and are therefore useful summary statistics for comparisons and formal testing. Indeed, unlike weighted versions of the traditional log score (Amisano and Giacomini, 2007), Gneiting and Ranjan (2011) scores retain propriety (see also Diks et al., 2011) and are amenable to standard statistical testing techniques.

Table 1 shows the average GR Scores for our model and the ratios of the corre-

Table 1 - Average GR Scores and GR Scores Ratios

	1 Quarter Ahead				1 Year Ahead			
	TFCI	GKP	PCA	NFCI	TFCI	GKP	PCA	NFCI
Uniform (w_0)	0.59	**1.17**	**1.03**	1.03	0.42	**1.31**	**1.12**	**1.13**
Center (w_1)	0.11	**1.18**	**1.03**	1.03	0.08	**1.31**	**1.09**	**1.13**
Tails (w_2)	0.13	**1.14**	**1.04**	**1.04**	0.09	**1.32**	**1.19**	1.14
Right Tail (w_3)	0.18	**1.13**	**1.04**	1.04	0.13	**1.22**	**1.10**	**1.09**
Left Tail (w_4)	0.18	**1.19**	1.02	1.04	0.13	**1.41**	**1.15**	**1.18**

Note: Average Gneiting and Ranjan (2011) scores for our model (TFCI) under different weighting functions: $w_0 = 1$; $w_1(\tau) = \tau(1-\tau)$; $w_2(\tau) = (2\tau - 1)^2$; $w_3(\tau) = \tau^2$; $w_4(\tau) = (1-\tau)^2$. Scores for the remaining models are reported as ratios to the respective TFCI score. A ratio > 1 indicates that a model performs worse than the TFCI, and numbers in bold denote statistically significant differences at the 10% confidence level or better using the same testing strategy as Diebold and Mariano (1995).

sponding scores of the other three models to ours, 1 and 4 quarters ahead. TFCI forecasts generally outperform all alternatives for all weighting functions and both horizons. For 1-quarter-ahead forecasts, the gains relative to PCA and the NFCI models are generally around 3%. GKP model performs considerably worse, notably in the centre and left tail of the predictive distribution, where the losses are close to 20%. The same pattern persists for 1-year-ahead forecasts, but in this case the performance gains of our forecasts compared to the alternative models are larger: notably, the gains in the left tail are 18% and over 40% relative to the NFCI and GKP models, respectively. For all ratios reported in Table 1, we test for equal forecast performance (as in Diebold and Mariano, 1995), relying on the asymptotic normality of the GR scores, and find that with very few exceptions, the differences are statistically significant at the 10% level or better. Overall, this suggests that 1-year-ahead forecasts exploiting financial information are less noisy than those for shorter horizons, or put differently, that the information extracted from our data is more relevant for longer horizons.

In the Online Appendix, we also report probability integral transforms (PITs) to assess calibration. As shown in Figure A.5, for 1-quarter-ahead forecasts, the NFCI, PCA and our model mostly fall within the 10% critical region of the test proposed by Rossi and Sekhposyan (2014), while GKP's model displays a clear tendency to over-predict GDP growth. That tendency is more pronounced for all models at the 1-year horizon, but even there, our model tends to do best in terms of relative ranking.

5 Conclusion

We propose a novel approach to extract factors from large data sets that maximize covariation with the quantiles of a target distribution of interest. We showcase our methodology by constructing *targeted* financial conditions indices for US GDP-at-risk and other portions of the predictive distribution, such as the median. We show that this yields indices that are economically intuitive, smoother when computed in real time, and with superior out-of-sample forecasting power compared to existing alternatives. While the application to financial conditions and GDP-at-risk is of special interest due to the existing literature on the subject and its continued policy relevance, our method is general and flexible and could easily be applied to other problems.

References

Adams, P. A., T. Adrian, N. Boyarchenko, and D. Giannone (2021): "Forecasting macroeconomic risks," *International Journal of Forecasting*, 37, 1173–1191.

Adrian, T., N. Boyarchenko, and D. Giannone (2019): "Vulnerable Growth," *American Economic Review*, 109, 1263–1289.

Amburgey, A. J. and M. W. McCracken (2023): "On the real-time predictive content of financial condition indices for growth," *Journal of Applied Econometrics*, 38, 137–163.

Amisano, G. and R. Giacomini (2007): "Comparing Density Forecasts via Weighted Likelihood Ratio Tests," *Journal of Business & Economic Statistics*, 25, 177–190.

Ando, T. and J. Bai (2020): "Quantile Co-Movement in Financial Markets: A Panel Quantile Model With Unobserved Heterogeneity," *Journal of the American Statistical Association*, 115, 266–279.

Ando, T. and R. S. Tsay (2011): "Quantile regression models with factor-augmented predictors and information criterion," *The Econometrics Journal*, 14, 1–24.

Arregui, N., S. Elekdag, R. G. Gelos, R. Lafarguette, and D. Seneviratne (2018): "Can Countries Manage Their Financial Conditions Amid Globalization?" IMF Working Papers 18/15, International Monetary Fund.

Arrigoni, S., A. Bobasu, and F. Venditti (2022): "Measuring Financial Conditions using Equal Weights Combination," *IMF Economic Review*, 70, 668–697.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): "The financial accelerator in a quantitative business cycle framework," in *Handbook of Macroeconomics*, ed. by J. B. Taylor and M. Woodford, Elsevier, vol. 1 of *Handbook of Macroeconomics*, chap. 21, 1341–1393.

Brave, S. and R. A. Butters (2011): "Monitoring financial stability: a financial conditions index approach," *Economic Perspectives*, 35, 22–43.

——— (2012): "Diagnosing the Financial System: Financial Conditions and Financial Stress," *International Journal of Central Banking*, 8, 191–239.

Chari, A., K. D. Stedman, and C. Lundblad (2020): "Capital Flows in Risky Times: Risk-on/Risk-off and Emerging Market Tail Risk," NBER Working Papers 27927, National Bureau of Economic Research, Inc.

Chen, L., J. J. Dolado, and J. Gonzalo (2021): "Quantile Factor Models," *Econometrica*, 89, 875–910.

Chi, T.-C., T.-H. Fan, R. M. Ghigliazza, D. Giannone, and Z. K. Wang (2025): "Forecasting Macroeconomic Risk with Big Data: A Machine Learning Approach," Mimeo.

Christiano, L., R. Motto, and M. Rostagno (2014): "Risk Shocks," *American Economic Review*, 104, 27–65.

Diebold, F. X. and R. S. Mariano (1995): "Comparing Predictive Accuracy," *Journal of Business & Economic Statistics*, 13, 253–263.

Diks, C., V. Panchenko, and D. van Dijk (2011): "Likelihood-based scoring rules for comparing density forecasts in tails," *Journal of Econometrics*, 163, 215–230.

Eguren-Martin, F., C. O'Neill, A. Sokol, and L. v. d. Berge (2021): "Capital flows-at-risk: push, pull and the role of policy," Working Paper Series 2538, European Central Bank.

Eguren-Martin, F. and A. Sokol (2022): "Attention to the Tail(s): Global Financial Conditions and Exchange Rate Risks," *IMF Economic Review*, 70, 487–519.

Figueres, J. M. and M. Jarociński (2020): "Vulnerable growth in the euro area: Measuring the financial conditions," *Economics Letters*, 191.

Gelos, G., L. Gornicka, R. Koepke, R. Sahay, and S. Sgherri (2022): "Capital flows at risk: Taming the ebbs and flows," *Journal of International Economics*, 134.

Gertler, M. and N. Kiyotaki (2010): "Financial Intermediation and Credit Policy in Business Cycle Analysis," in *Handbook of Monetary Economics*, ed. by B. M. Friedman and M. Woodford, Elsevier, vol. 3 of *Handbook of Monetary Economics*, chap. 11, 547–599.

Giacomini, R. and I. Komunjer (2005): "Evaluation and Combination of Conditional Quantile Forecasts," *Journal of Business & Economic Statistics*, 23, 416–431.

Giglio, S., B. Kelly, and S. Pruitt (2016): "Systemic risk and the macroeconomy: An empirical evaluation," *Journal of Financial Economics*, 119, 457–471.

Gilchrist, S. and E. Zakrajsek (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

Gneiting, T. and R. Ranjan (2011): "Comparing Density Forecasts Using Threshold- and Quantile-Weighted Scoring Rules," *Journal of Business & Economic Statistics*, 29, 411–422.

Haberis, A. and A. Sokol (2014): "A procedure for combining zero and sign restrictions in a VAR-identification scheme," Discussion Papers 1410, Centre for Macroeconomics (CFM).

Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz, and M. W. Watson (2010): "Financial Conditions Indexes: A Fresh Look after the Financial Crisis," Tech. rep.

IMF (2017): "Global Financial Stability Report," Tech. rep., International Monetary Fund.

Koenker, R. and J. A. F. Machado (1999): "Goodness of Fit and Related Inference Processes for Quantile Regression," *Journal of the American Statistical Association*, 94, 1296–1310.

Koenker, R. W. and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

Kremer, M., M. Lo Duca, and D. Holló (2012): "CISS - a composite indicator of systemic stress in the financial system," Working Paper Series 1426, European Central Bank.

Plagborg-Møller, M., L. Reichlin, G. Ricco, and T. Hasenzagl (2020): "When is Growth at Risk?" *Brookings Papers on Economic Activity*, 2020, 167–229, replication code and data (6 GB).

Rossi, B. and T. Sekhposyan (2014): "Evaluating predictive densities of US output growth and inflation in a large macroeconomic data set," *International Journal of Forecasting*, 30, 662 – 682.

Schularick, M. and A. M. Taylor (2012): "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," *American Economic Review*, 102, 1029–1061.

A Online Appendix

Table A.1 - List of Indicators comprising the Chicago Fed's National Financial Conditions Index

Risk Indicators

1) 1-mo. Asset-backed/Financial commercial paper spread
2) BofAML Home Equity ABS/MBS yield spread
3) 3-mo. Financial commercial paper/Treasury bill spread
4) Commercial Paper Outstanding
5) BofAML 3-5 yr AAA CMBS OAS spread
6) Counterparty Risk Index (formerly maintained by Credit Derivatives Research)
7) ICE BofAML ABS/5-yr Treasury yield spread
8) 3-mo./1-wk AA Financial commercial paper spread
9) ICE BofAML Financial/Corporate Credit bond spread
10) ICE BofAML Mortgage Master MBS/10-year Treasury yield spread
11) Treasury Repo Delivery Fails Rate
12) Agency Repo Delivery Failures Rate
13) Corporate Securities Repo Delivery Failures Rate
14) Agency MBS Repo Delivery Failures Rate
15) FDIC Volatile Bank Liabilities
16) 3-mo. Interbank Deposit Spread (OBFR/LIBID-Treasury)
17) On-the-run vs. Off-the-run 10-yr Treasury liquidity premium
18) Total Money Market Mutual Fund Assets/Total Long-term Fund Assets
19) Fed Funds/Overnight Treasury Repo rate spread
20) Fed Funds/Overnight Agency Repo rate spread
21) Repo Market Volume (Repurchases+Reverse Repurchases of primary dealers)
22) Fed Funds/Overnight MBS Repo rate spread
23) 3-mo./1-wk Treasury Repo spread
24) 10-yr/2-yr Treasury yield spread
25) 2-yr/3-mo. Treasury yield spread
26) 10-yr Interest Rate Swap/Treasury yield spread
27) 2-yr Interest Rate Swap/Treasury yield spread
28) 3-mo. Overnight Indexed Swap (OIS)/Treasury yield spread
29) 3-mo. LIBOR/CME Term SOFR-Treasury spread
30) 1-yr./1-mo. LIBOR/CME Term SOFR spread
31) Advanced Foreign Economies Trade-weighted US Dollar Value Index
32) CBOE Market Volatility Index VIX
33) 1-mo. BofAML Option Volatility Estimate Index
34) 3-mo. BofAML Swaption Volatility Estimate Index

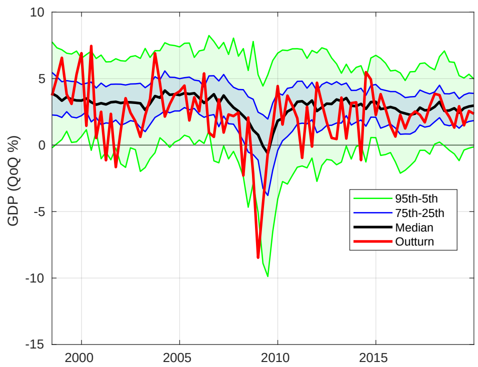
Credit Indicators

35) 1-mo. Nonfinancial commercial paper A2P2/AA credit spread
36) Moody's Baa corporate bond/10-yr Treasury yield spread
37) UM Household Survey: Auto Credit Conditions Good/Bad spread
38) Commercial Bank 48-mo. New Car Loan/2-yr Treasury yield spread
39) Commercial Bank 24-mo. Personal Loan/2-yr Treasury yield spread
40) S&P US Bankcard Credit Card: 3-mo. Delinquency Rate
41) Consumer Credit Outstanding
42) S&P US Bankcard Credit Card: Excess Rate Spread
43) FRB Senior Loan Officer Survey: Tightening Standards on Large C&I Loans
44) FRB Senior Loan Officer Survey: Tightening Standards on Small C&I Loans
45) FRB Senior Loan Officer Survey: Tightening Standards on CRE Loans
46) S&P US Bankcard Credit Card: Receivables Outstanding
47) FRB Senior Loan Officer Survey: Willingness to Lend to Consumers
48) NY Fed Consumer Credit Panel: Loan Delinquency Status: Non-current (% of Total Balance)
49) American Bankers Association Value of Delinquent Consumer Loans/ Total Loans
50) American Bankers Association Value of Delinquent Home Equity Loans/ Total Loans
51) American Bankers Association Value of Delinquent Credit Card Loans/ Total Loans
52) UM Household Survey: Durable Goods Credit Conditions Good/Bad spread
53) Finance Company Owned & Managed Receivables
54) UM Household Survey: Mortgage Credit Conditions Good/Bad spread
55) BofAML High Yield/Moody's Baa corporate bond yield spread
56) 30-yr Jumbo/Conforming fixed rate mortgage spread
57) Markit High Yield (HY) 5-yr Senior CDS Index
58) Markit Investment Grade (IG) 5-yr Senior CDS Index
59) MBA Serious Delinquencies
60) Money Stock: MZM
61) 30-yr Conforming Mortgage/10-yr Treasury yield spread
62) Bond Market Association Municipal Swap/State & Local Government 20-yr GO bond spread
63) NACM Survey of Credit Managers: Credit Manager's Index
64) Commercial Bank Noncurrent/Total Loans
65) FRB Senior Loan Officer Survey: Tightening Standards on RRE Loans
66) NFIB Survey: Credit Harder to Get
67) FRB Senior Loan Officer Survey: Increasing spreads on Large C&I Loans
68) FRB Senior Loan Officer Survey: Increasing spreads on Small C&I Loans
105) CBOE Crude Oil Volatility Index, OVX

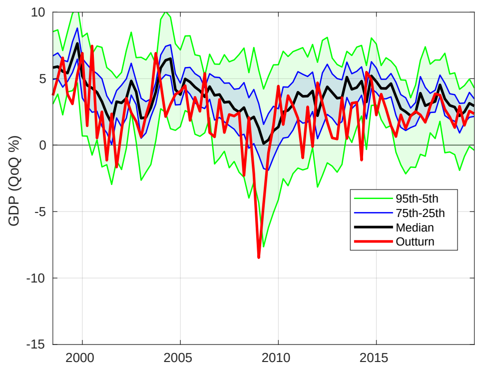
Leverage Indicators

69) Nonmortgage ABS Issuance (Relative to 12-mo. MA)
70) Broker-dealer Debit Balances in Margin Accounts
71) New US Corporate Debt Issuance (Relative to 12-mo. MA)
72) Commercial Bank C&I Loans/Total Assets
73) CMBS Issuance (Relative to 12-mo. MA)
74) COMEX Gold/NYMEX WTI Futures Market Depth
75) Commercial Bank Consumer Loans/Total Assets
76) FRB Commercial Property Price Index
77) 10-yr Constant Maturity Treasury yield
78) Commercial Bank Total Unused C&I Loan Commitments/Total Assets
79) Net Notional Value of Credit Derivatives
80) CME E-mini S&P Futures Market Depth
81) Total Assets of Finance Companies/GDP
82) Total Assets of Funding Corporations/GDP
83) S&P 500 Financials/S&P 500 Price Index (Relative to 2-yr MA)
84) Total Agency and GSE Assets/GDP
85) Total Assets of Insurance Companies/GDP
86) Fed funds and Reverse Repurchase Agreements/Total Assets of Commercial Banks
87) CoreLogic National House Price Index
88) New State & Local Government Debt Issues (Relative to 12-mo.h MA)
89) Total MBS Issuance (Relative to 12-mo. MA)
90) S&P 500, NASDAQ, and NYSE Market Capitalization/GDP
91) S&P 500, S&P 500 mini, NASDAQ 100, NASDAQ mini Open Interest
92) 3-mo. Eurodollar, 10-yr/3-mo. swap, 2-yr and 10-yr Treasury Open Interest
93) Total Assets of Pension Funds/GDP
94) CME Eurodollar/CBOT T-Note Futures Market Depth
95) Total REIT Assets/GDP
96) Commercial Bank Real Estate Loans/Total Assets
97) Total Assets of Broker-dealers/GDP
98) Commercial Bank Securities in Bank Credit/Total Assets
99) New US Corporate Equity Issuance (Relative to 12-mo. MA)
100) Federal, state, and local debt outstanding/GDP
101) Total Assets of ABS issuers/GDP
102) Wilshire 5000 Stock Price Index
103) Household debt outstanding/PCE Durables and Residential Investment
104) Nonfinancial business debt outstanding/GDP

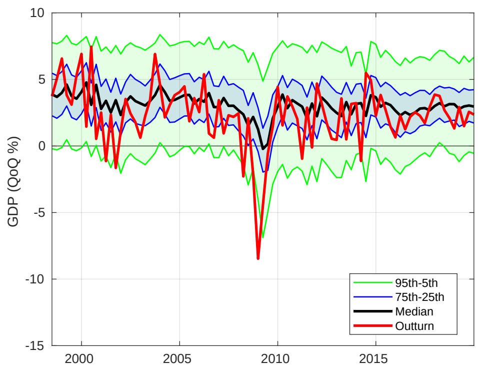
Figure A.1 Model Forecasts vs. Outturns, 1 Quarter Ahead



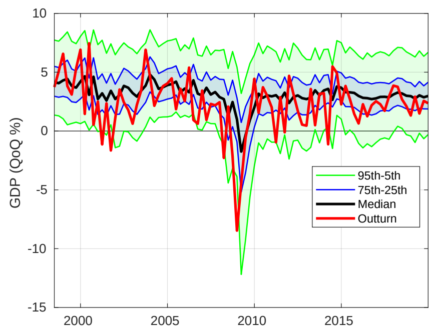
(a) TFCI



(b) GKP



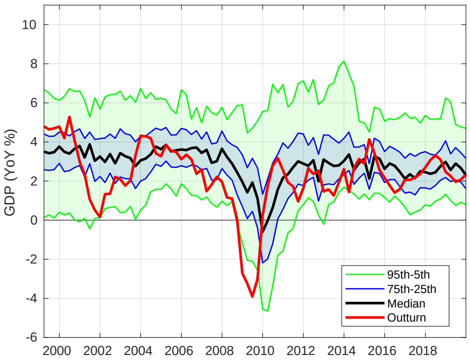
(c) PCA



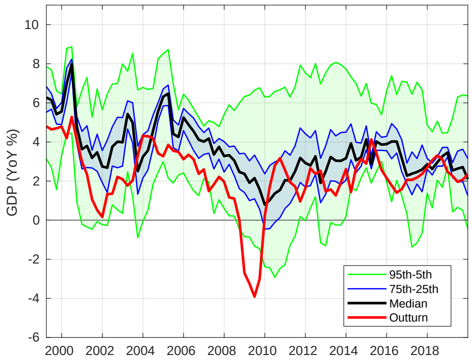
(d) NFCI

Note: Predictive densities compared to the outturn one quarter ahead. The quarter-on-quarter growth rate is seasonally-adjusted and annualized.

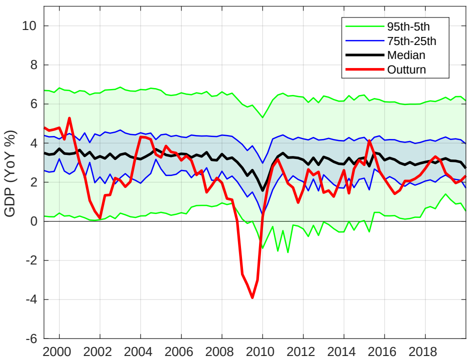
Figure A.2 Model Forecasts vs. Outturns, 1-Year-Ahead



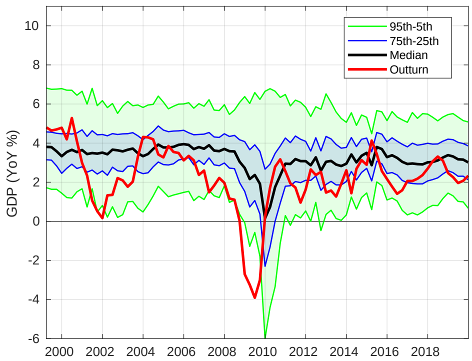
(a) TFCI



(b) GKP



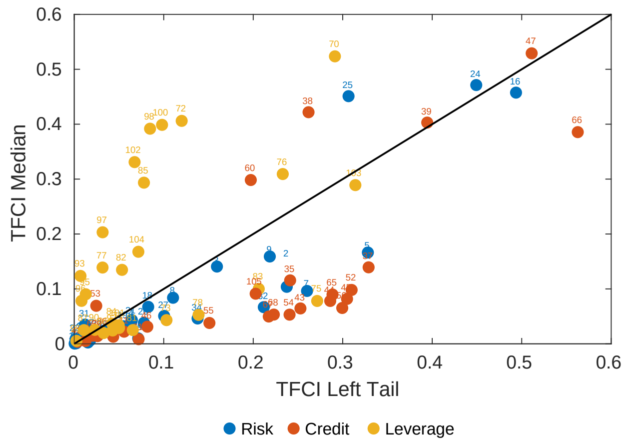
(c) PCA



(d) CFNFCI

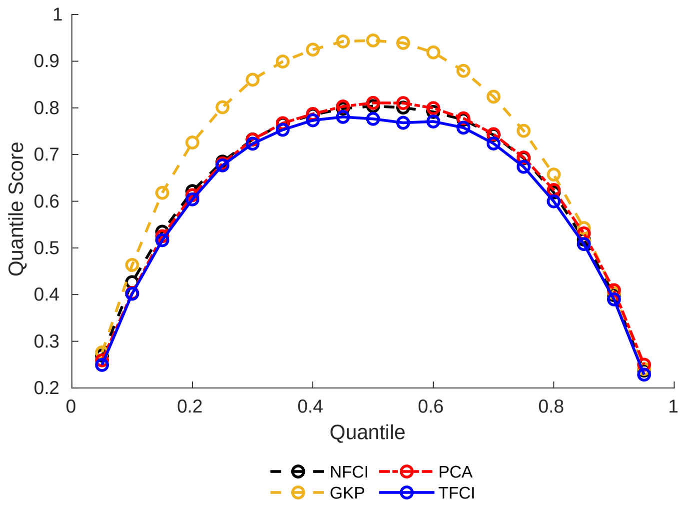
Note: Predictive densities compared to the outturn one year ahead.

Figure A.3 Average ex-ante TFCI squared loadings, median vs. left tail



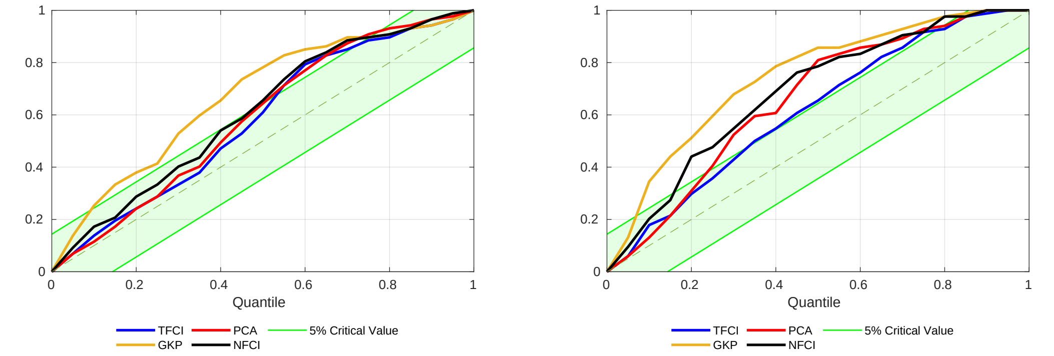
Note: Sample averages of ex-ante squared loadings of the Left Tail TFCI and the Median TFCI. See Table A.1 for the series' legends.

Figure A.4 Average Quantile Scores



Note: Average quantile scores, 1 quarter ahead. Lower values represent better performance.

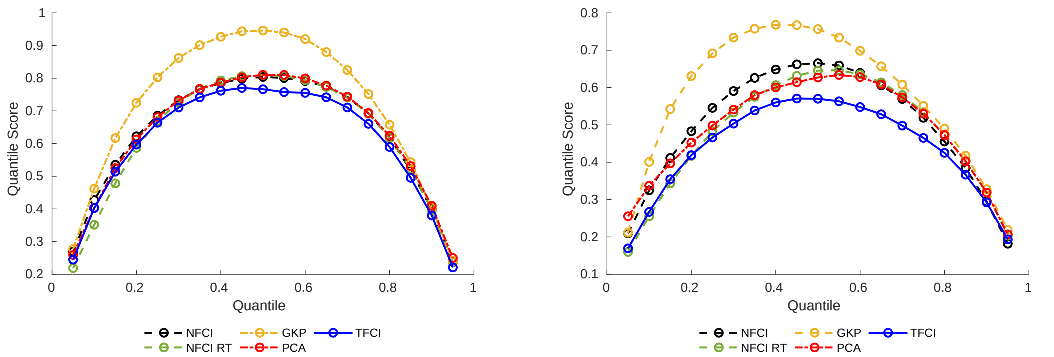
Figure A.5 Probability Integral Transforms (PITs)



(a) 1 Quarter Ahead **(b)** 1 Year Ahead

Note: Probability integral transforms (PITs). The green area represents the 10% critical region, as in Rossi and Sekhposyan (2014). An ideally-calibrated model lies on the diagonal throughout the quantiles, so the closer to it, the better.

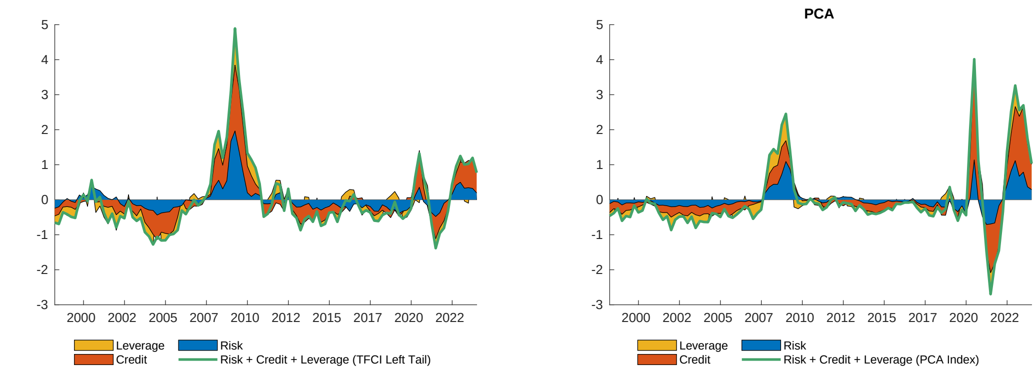
Figure A.6 Average Quantile Scores (vs. Real Time NFCI)



(a) 1 Quarter Ahead **(b)** 1 Year Ahead

Note: Average quantile scores, 1 quarter and 1 year ahead. Lower values represent better performance. NFCI RT based on vintages from Amburgey and McCracken (2023).

Figure A.7 Left tail TFCI and PCA index - 1 Year Ahead (Covid Sample)

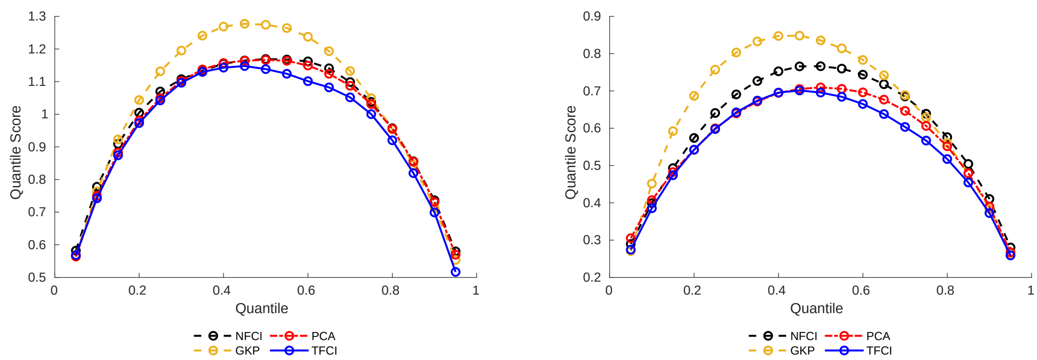


(a) TFCI left tail index

(b) PCA index

Note: Ex-ante time series of the a) Left Tail TFCI (5th Percentile) and b) PCA Index, when forecasting 1 year ahead. Contributions from leverage (yellow), credit (red) and risk (blue) are also shown. Both indices have been standardized.

Figure A.8 Average Quantile Scores (Covid Sample)



(a) 1 Quarter Ahead

(b) 1 Year Ahead

Note: Average quantile scores, 1 quarter and 1 year ahead. Lower values represent better performance.