# Bank of England

# Targeted financial conditions indices and growth-at-risk

**Staff Working Paper No. 1,084**

July 2024

Fernando Eguren-Martin, Sevim Kösem, Guido Maia and Andrej Sokol

# Bank of England

# Targeted financial conditions indices and growth-at-risk

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

## Abstract

We propose a novel approach to extract factors from large data sets that maximise covariation with the quantiles of a target distribution of interest. From the data underlying the Chicago Fed's National Financial Conditions Index, 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. 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.

---

(1) SPX Capital.
(2) Bank of England, Centre for Macroeconomics and Systemic Risk Centre.
(3) Centre for Macroeconomics and London School of Economics.
(4) Bloomberg LP. Email: asokol14@bloomberg.net (corresponding author)

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

# 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, 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). Financial conditions indices 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 preexisting 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 financial indicators – 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 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.

Both the "at-risk" papers cited above and our own approach can be categorized as quantile regression models with factor-augmented predictors (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) is, to our knowledge, the only paper that shares our goal, namely to extract information from a panel of variables based on covariation with the quantiles of a target variable of interest. 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 focusing on fitting the quantiles of the target variable.

---

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

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 a 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.

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 $\Lambda$ is a $n \times n$ matrix of factor loadings. Any orthonormal rotation of $\Lambda$ 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 $\theta$. 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 $\Lambda$ 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 $\theta$.[3]

Now consider the following specification of the conditional quantile function of

---

[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.

response variable $y_{t+h}$ for quantile $\tau$:

$$Q\left(y_{t+h}|w_t,\ \tilde{f}_t\left(\theta_\tau\right),\tau\right) = \alpha_\tau' w_t + \gamma_\tau'\left(\theta_\tau\right) s_\tau \tilde{f}_t\left(\theta_\tau\right)$$

$$= \begin{bmatrix} \alpha_\tau' & \gamma_\tau'\left(\theta_\tau\right) \end{bmatrix} \begin{bmatrix} w_t \\ s_\tau \tilde{f}_t\left(\theta_\tau\right) \end{bmatrix}$$

$$\equiv \beta_\tau'\left(\theta_\tau\right) x_t\left(\theta_\tau\right) \tag{5}$$

Here $w_t$ captures any explanatory variables not included in $z_t$, such as deterministic terms or lagged values of $y_t$, and $s_\tau$ 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 modelling 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 $\theta_\tau$, $\hat{\beta}_\tau\left(\theta_\tau\right)$ solves the quantile regression problem

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

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 $\theta_\tau^*$, the set of angles, and therefore rotated factors, that, given a choice of $r$ and $s$, maximises the fit of the model:

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

$\theta_\tau^*$ is not available in closed form, but can be recovered by numerical optimization.[5]

---

[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.

[5] We provide replication codes in MATLAB for the purpose.

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

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

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

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

In order 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 (including the underlying data used), then discuss their main features and differences with respect to existing 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.[6] The authors group the series into three categories: leverage, credit and risk; we follow that categorization in our

---

[6]We downloaded the underlying contributions to the NFCI from Bloomberg, using **ALLX NFCI <GO>**. The same contributions, from 2008 onwards, are also available on the Chicago Fed website here.

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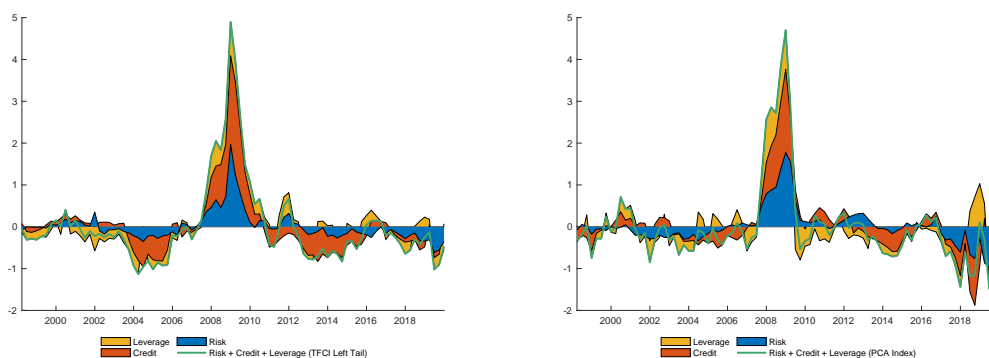


**(a)** TFCI left tail index

**(b)** PCA index

*Note*: The figures plot the real-time (ex ante) time series of the a) Left Tail TFCI (5th Percentile) and b) PCA Index, when forecasting 1 year ahead. The indices comprise three subgroups: leverage (yellow), credit (red) and risk (blue). Both indices have been standardized.

color-coding in subsequent charts.[7] We start by standardising the underlying contributions to then extract principal components, which we use both as a benchmark and as the initial orthogonalization to initialize our method (see Section 2).[8]

We focus on a range of quantiles of GDP growth both 1-quarter and 4-quarters ahead, in line with the literature.[9] For each, the specification of our model is 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 $s = 1$). 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.[10]

---

[7]See Appendix 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 at least 25% of the series comprising the final dataset are available.

[8]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).

[9]1 quarter ahead, the left-hand side variable is the seasonally-adjusted QoQ annualized growth rate; 1 year ahead, it is the YoY growth rate.

[10]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

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

In this subsection we focus on the $5^{th}$ percentile of the distribution of US GDP growth four quarters ahead, one possible definition of growth-at-risk (see, for example, IMF, 2017).

Figure 1 shows the real-time[11] evolution of the TFCI that results from targeting the $5^{th}$ percentile of GDP growth four quarters ahead, decomposed into the contributions of each financial category. The right panel shows an analogous figure 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.[12] 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 the 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

---

filter out some idiosyncratic variation from the financial variables before focusing on covariation with individual quantiles of our target.

[11]Or ex-ante, as opposed to the ex post series fitting the realised data that is used at the estimation step.

[12]For each period, the contributions to the index are obtained by inverting $\tilde{\Lambda}\left(\theta_\tau^*\right)$ and multiplying the elements of the first row by the original (standardized) underlying series.

**Figure 2** Average Real-Time Squared Loadings, 1 Year Ahead
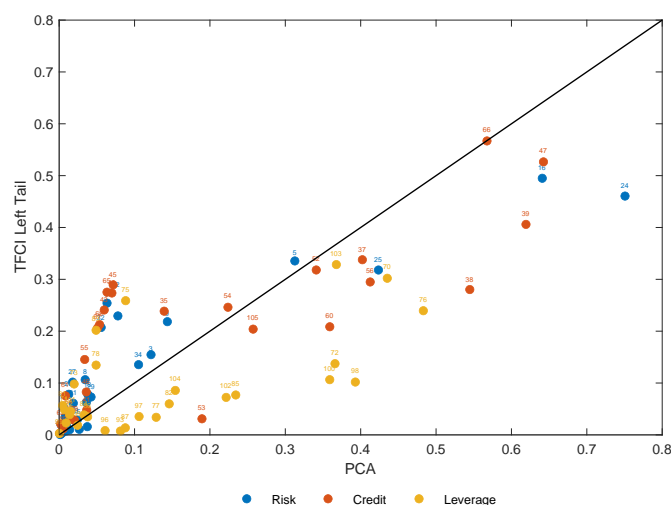


*Note*: Sample averages of real-time (ex ante) squared loadings for the PCA vs. Left Tail TFCI indices, when forecasting 1 year ahead. Each dot corresponds to one component series. See Appendix for the series' legends.

does not imply causation, it is nevertheless suggestive and can be associated to 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.[13] Each dot corresponds to one of the component series, colour-coded according to the three broad groups they belong to.[14] 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.

Two features of Figure 2 stand out. First, our index appears less clearly associated with the developments of a small set of variables compared to PCA. 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

---

[13]In each vintage, squared loadings correspond to the share of variance of each indicator explained by the targeted index.

[14]A table matching indicator numbers to each one of the series can be found in the Appendix.

less strongly with indicators of leverage, and more strongly with credit and risk indicators, corroborating 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 NFIB and 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, the left panel of 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 tracks more closely business cycle developments, and displays more even contributions from the three types of components. This is corroborated by the right panel of Figure 3, which compares the squared loadings of each series on the median-based TFCI with its left-tail counterpart. 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, this section shows that financial conditions indices based on common variation across financial variables tend to be associated with a small number of indicators, and that this does not match variation extracted *optimally* for forecasting individual quantiles of the distribution of GDP growth. Our targeted financial conditions indices, when applied separately to the left tail and median of future GDP growth, show that different types of financial variables contain relevant information for each. Leverage-type variables are more important for forecasting the centre of the predictive distribution, while risk and credit variables are more important for forecasting left-tail events. After revisiting this narrative evidence, we next turn to the out-of-sample forecasting performance of our TFCIs.

**Figure 3** Median TFCI - 1 Year Ahead
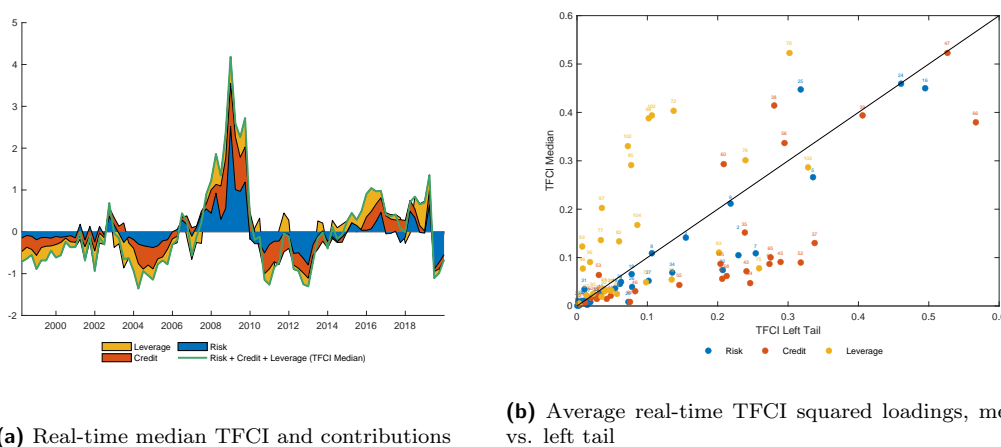


**(a)** Real-time median TFCI and contributions

**(b)** Average real-time TFCI squared loadings, median vs. left tail

*Note*: Panel (a) shows the real-time (ex ante) Median TFCI time series and the contributions of each subgroup. Panel (b) compares the sample averages of real-time (ex ante) squared loadings of the Left Tail TFCI and the Median TFCI.

# 4   Out-of-Sample Performance

In this section we evaluate the out-of-sample forecasting performance of our method for US GDP growth, considering 1- and 4-quarters-ahead forecasts. We compare our approach to three alternatives: a model that relies on the Chicago Fed's NFCI, that is, the specification used by 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).[15] 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 Great Financial Crisis.[16] To avoid look-ahead bias in the

---

[15]Giglio et al. (2016) propose an approach, called partial quantile regression, which seeks to summarize the cross section of (financial) predictors according to their covariation with a chosen quantile of the target. In spirit, it is therefore the approach closest to ours. In practice, however, we show that on our dataset at least, their approach is not competitive with any of the alternatives, including our model.

[16]Although the overall results are robust to it, we chose not to include the pandemic period in

**Figure 4** - TFCI Forecasts vs. Outturns



**(a)** 1 quarter ahead
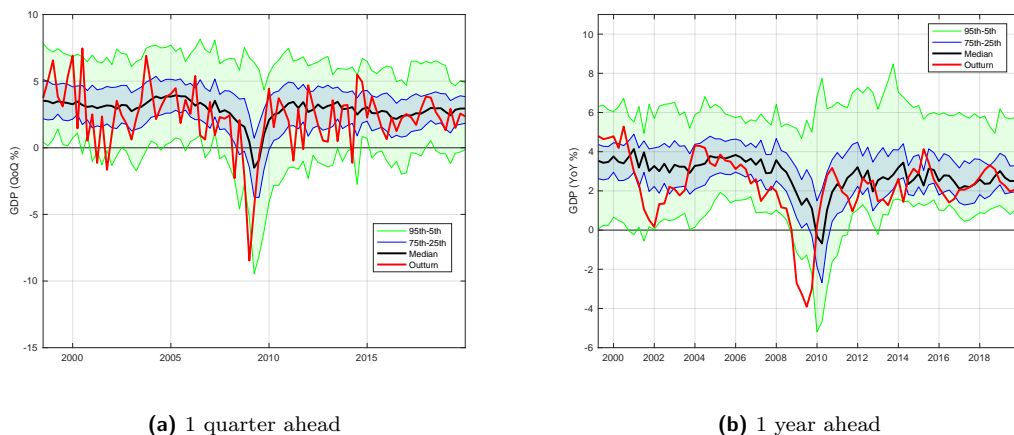
**(b)** 1 year ahead

*Note*: Selected predictive quantiles based on TFCIs over time against outturns, a) 1 quarter and b) 1 year ahead. The QoQ growth rate is seasonally-adjusted and annualized.

construction of the 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 means fewer financial variables enter the indices in earlier samples than in later ones.[17] For the NFCI, we currently use the 2019Q4 vintage up to the forecast date in each vintage; this benchmark therefore suffers from look-ahead bias and puts it at an advantage relative to the other models. As Adams et al. (2021), we abstract from the issue of GDP revisions and simply use the 2019Q4 vintage consistently across models.

Figure 4 shows data outturns against estimated predictive densities constructed using our approach, and we provide similar pictures for the other models in the Appendix. To compare the performance of these predictive densities across models, we focus on three evaluation metrics: (i) quantile scores, (ii) a set of quantile-weighted scores proposed by Gneiting and Ranjan (2011), and (iii) probability integral transforms (PITs).

---

our evaluation sample, as the GDP dynamics during that period were not matched by developments in financial conditions that could have helped predicting them. Results are available upon request.

[17]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.

**Figure 5** Average Quantile Scores

**(a)** 1 Quarter Ahead          **(b)** 1 Year Ahead
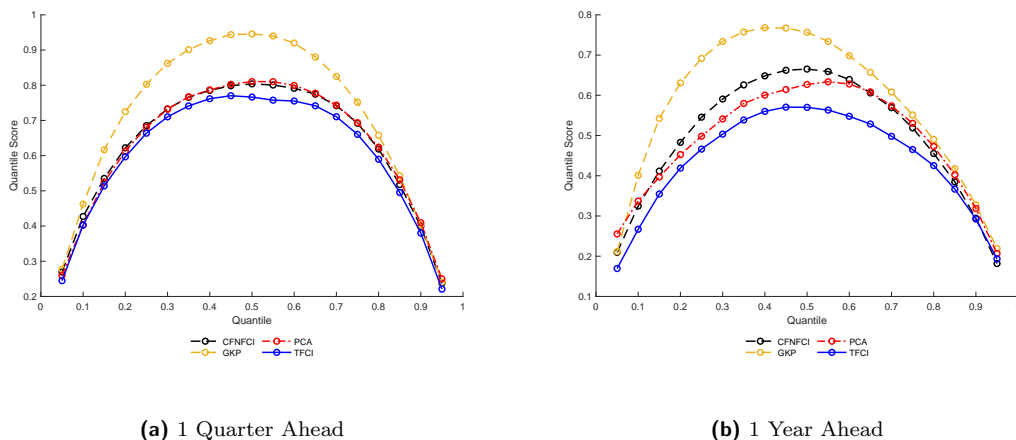
*Note*: Average quantile scores for all models, a) 1 quarter and b) 1 year ahead. Lower values represent better performance.

The quantile score (or tick loss function, see Giacomini and Komunjer, 2005) is defined as

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

The score penalises outturns that are more extreme (i.e. fall further in the corresponding tail) than the predictive quantile $\hat{P}_{v,h}^{-1}(\tau)$. 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 5. 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 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 of the predictive distribution.

Gneiting and Ranjan (2011) also propose a set of quantile-weighted versions of continuously ranked probability scores to assess forecasting performance in specific

13

regions of the predictive distribution. The general form of their scores is

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

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.[18]

Table 1 shows the average GR Scores for our model and the ratios of the corresponding 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, the main focus of the "at-risk" literature, are generally around 5%. GKP performs considerably worse, notably in the centre and left tail of the predictive distribution, where the losses are around 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: the gains in the left tail are 17% and 40% relative to the NFCI and GKP, respectively.[19] For all ratios reported in Table 1, we test for equal forecast performance (as in Diebold and Mariano, 1995, Amisano and Giacomini, 2007), relying on the asymptotic normality of the GR scores, and find that with very few exceptions, the differences we report are statistically significant at the 10% level or better.

Finally, we also compute probability integral transforms (PITs), defined as

$$u_{v,h} = \int_{-\infty}^{y_{t_v+h}} \hat{p}_{v,h}(x) dx \equiv \hat{P}_{v,h}(y_{t_v+h}) \tag{11}$$

where $\hat{p}_{v,h}(\cdot)$ is the predictive density function estimated in vintage $v$ for forecast horizon $h$, and $\hat{P}_{v,h}(\cdot)$ the corresponding cumulative distribution function. An

---

[18]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.

[19]This chimes with the notion 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.

**Table 1** - Average GR Scores and GR Scores Ratios

| | 1 Quarter Ahead | | | | 1 Year Ahead | | | |
|---|---|---|---|---|---|---|---|---|
| | TFCI | GKP | PCA | NFCI | TFCI | GKP | PCA | NFCI |
| Uniform ($w_0$) | 0.58 | **1.19** | **1.05** | **1.05** | 0.42 | **1.32** | **1.12** | **1.14** |
| Center ($w_1$) | 0.11 | **1.20** | **1.05** | **1.04** | 0.08 | **1.33** | **1.11** | **1.15** |
| Tails ($w_2$) | 0.13 | **1.16** | **1.05** | **1.06** | 0.10 | **1.29** | **1.16** | 1.12 |
| Right Tail ($w_3$) | 0.18 | **1.16** | **1.06** | **1.05** | 0.13 | **1.23** | **1.11** | **1.10** |
| Left Tail ($w_4$) | 0.18 | **1.21** | 1.04 | 1.05 | 0.13 | **1.40** | **1.15** | **1.17** |

*Note*: The table shows average Gneiting and Ranjan (2011) scores for our model (TFCI) and for 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), Amisano and Giacomini (2007).

ideally-calibrated model should deliver a sequence of predictive distributions whose PITs are distributed uniformly over the unit interval, that is, should lie on the diagonal of each panel of Figure 6.

For 1-quarter-ahead forecasts (left panel), the NFCI, PCA and our model mostly fall within the 10% critical region of test proposed by Rossi and Sekhposyan (2014), while GKP displays a clear tendency to over-predict GDP growth (too many outcomes fall in the lower tail). The tendency to over-predict GDP growth 1 year ahead (right panel) is more pronounced for all models, but even where our model lies outside of the critical region, it still tends to be the better-calibrated one.

# 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 targeted financial conditions indices that are economically intuitive, smoother when computed in real time, and with superior out-of-sample forecasting power compared to existing alternatives.

**Figure 6** Probability Integral Transforms (PITs)



**(a)** 1 Quarter Ahead           **(b)** 1 Year Ahead
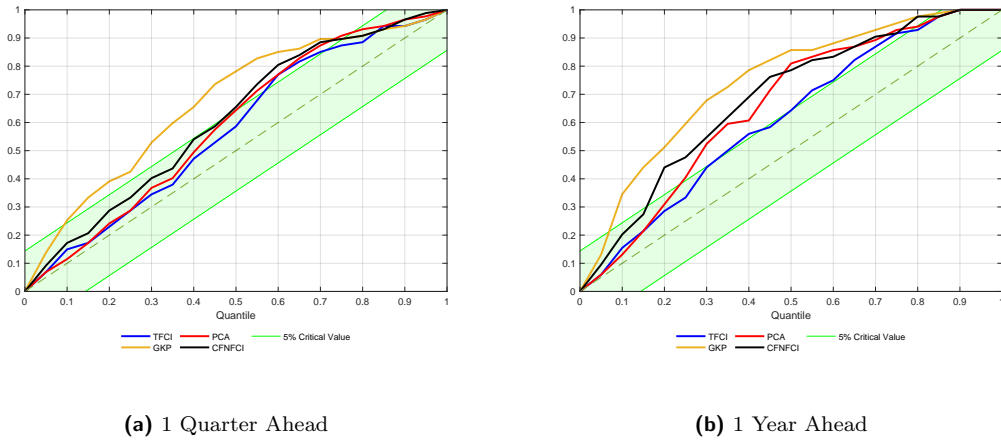
*Note*: The charts show the probability integral transforms (PITs) for each model and for both predictive horizons. The green band represents the 10% critical region, as in Rossi and Sekhposyan (2014). An ideally-calibrated model lies on the diagonal throughout the quantiles, so the closer to it, the better.

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 be easily applied to other problems as well.

# 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. SENEVI-RATNE (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.

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 Appendix

**Table A.1** - List of Indicators comprising the NFCI, by Group

**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 (Percent 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

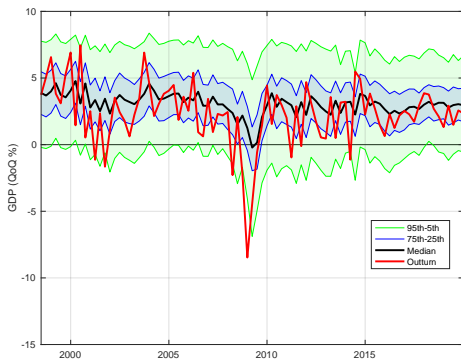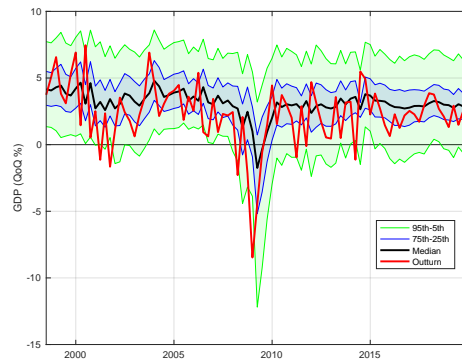**Figure A.1** Model Forecasts vs. Outturns, 1 Quarter Ahead
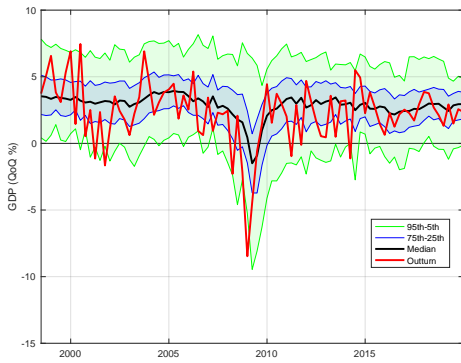


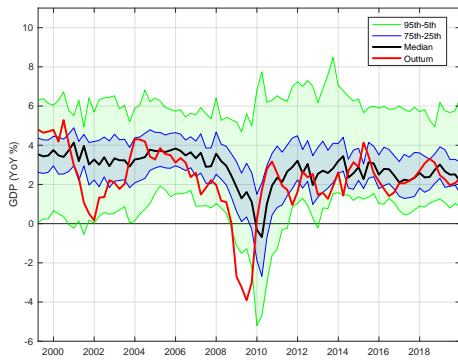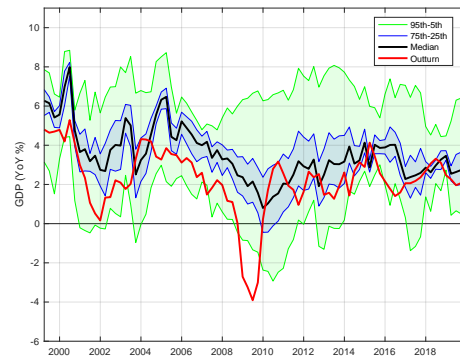**(a)** TFCI
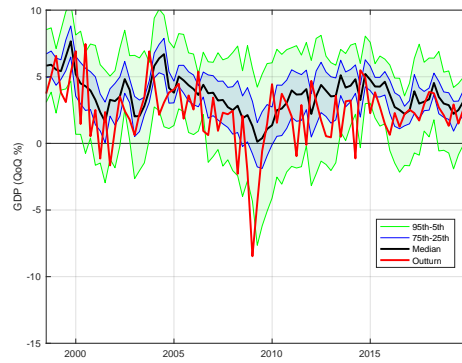
**(b)** GKP

**(c)** PCA

**(d)** CFNFCI

*Note*: Predictive densities time series for each model compared to the outturn one quarter ahead. The QoQ growth rate is seasonally-adjusted and annualized.
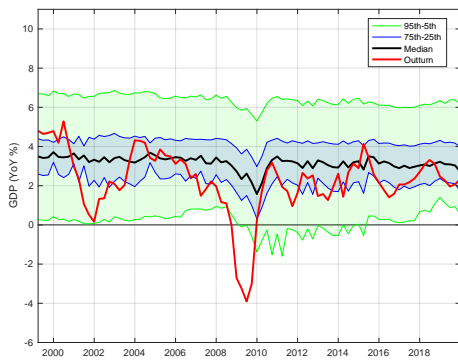
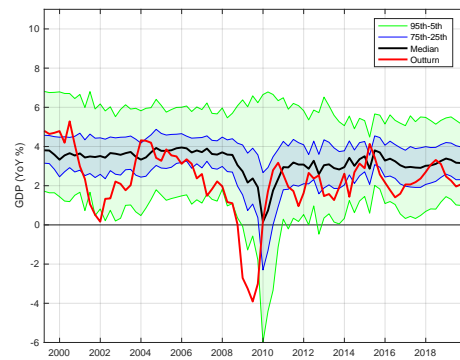**Figure A.2** Model Forecasts vs. Outturns, 1 Year Ahead



**(a)** TFCI

**(b)** GKP

**(c)** PCA

**(d)** CFNFCI

*Note*: Predictive densities time series for each model compared to the outturn one year ahead.