Modeling and Forecasting Macroeconomic Downside Risk

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Empirical motivation

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- Policy making based on *'plan for the worst, hope for the best'* approach heavily relies on appropriate assessment of downside risk
  - ↪ The degree of asymmetry of future GDP distributions undoubtedly plays an important role here.
- Policy makers are regularly called on assessing and communicating the "balance" between downside and upside risks when they present their views, and often rely on judgement in reaching their conclusions.

What do we model?

Time variation in GDP growth stems from two sources:

↪ **Cyclical variation**, reflecting how the economy response to business cycle shocks;

- Financial market turmoil (Christiano et al. 2010)

↪ **Secular movements** in the moments of the long-run distribution:

- Growth slowdown (Antolin-Diaz et al. 2017)
- Great Moderation (McConnell & Perez-Quiros 2000)
- Deepening skewness (Jensen et al. 2020)

In this paper

We model the full conditional distribution of GDP growth:

- Flexible asymmetric distribution (Asymmetric Student-t);
- Direct modeling of time-varying location, scale and asymmetry;
- We model permanent and transitory components;
- Exogenous predictors in the moments of the distribution.

Overview of the results

- GDP growth features significant time-varying asymmetry:
  - ↪ **Recessions** are characterized by higher variance, lower mean and deepening **(negative) asymmetry**;
  - ↪ Decreasing skewness over the last 25 years accounts for large share of long-run growth slowdown since early 2000s;
  - ↪ Covid shocks are tail shocks.

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  - ↪ Covid shocks are tail shocks.
- Modelling asymmetry increases out-of-sample forecast accuracy:
  - ↪ Our preferred model outperforms competitive benchmarks at the One-quarter and One-year horizon.
- Financial indicators increase estimation and prediction accuracy:
  - ↪ Increasing leverage predict increasing increasingly negative skewness in GDP growth.

Some relevant literature

Skewness in Business cycle fluctuations:
Hamilton (1989), Morley & Piger (2012), Jensen et al. (2020), Salgado et al. (2019).

Financial conditions predict (downside risk to) GDP growth:
Adrian et al. (2019), Giglio et al. (2016), De Nicolò & Lucchetta (2017), Galvão & Owyang (2018), Caldara et al. (2020).

↪ Brownlees & Souza (2020), Hasenzagl et al. (2020) and Plagborg-Møller et al. (2020) argue that these links are weak and do not hold out-of-sample.

Macro theory:
Bekaert & Engstrom (2017), Fernández-Villaverde et al. (2019), Fernández-Villaverde & Guerrón-Quintana (2020).

Model

Time-varying distribution of GDP growth

$$y_t = \mu_t + \sigma_t \varepsilon_t \quad \varepsilon_t \sim skt_\nu(0, 1, \varrho_t)$$

$\hookrightarrow$ μ_t: location

$\hookrightarrow$ σ_t: scale

$\hookrightarrow$ ϱ_t: shape

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The error term follows a Skew-t à la Gómez et al. (2007)

$$\ell_t(\Delta y_t|\theta, Y_{t-1}) = c(\eta) - \frac{1}{2}\log\sigma_t^2 - \frac{1+\eta}{2\eta}\log\left[1 + \frac{\eta\varepsilon_t^2}{(1-sgn(\varepsilon_t)\varrho_t)^2\sigma_t^2}\right]$$

where $sgn(x)$ is the sign of x, and $\nu = 1/\eta$ are the dof.

Score-driven time-varying parameters

- We model $f_t = (\mu_t, \gamma_t, \delta_t)'$, where $\gamma_t = \ln \sigma_t$ and $\delta_t = \operatorname{atanh} \varrho_t$ (to ensure $\sigma_t > 0$ and $\varrho_t \in [-1, 1]$);

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- Parameters' time variation is driven by the conditional score, s_t, (as in Creal et al. 2013, Harvey 2013):

$$f_{t+1} = \beta f_t + \alpha s_t$$

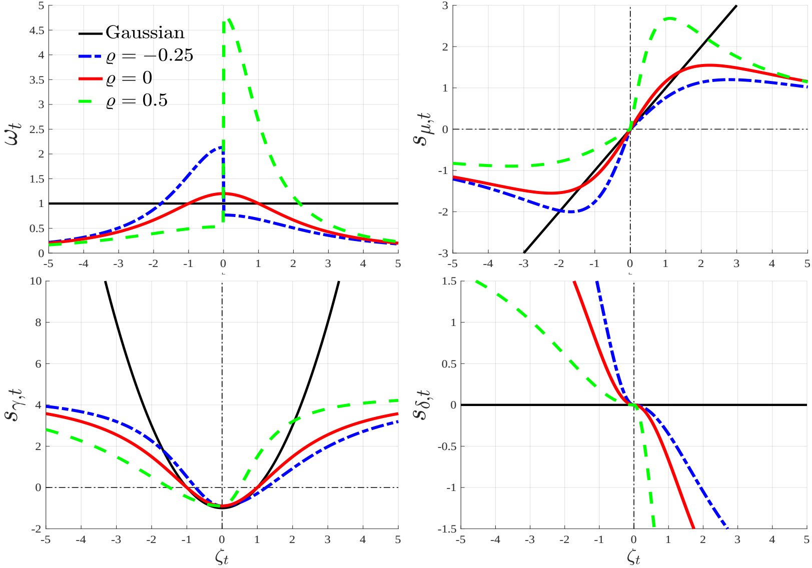
where $s_t = \mathcal{S}_{t-1} \nabla_t$, $\nabla_t = \frac{\partial \ell_t}{\partial f_t}$, and $\mathcal{S}_{t-1} = \mathcal{I}_{t-1}^{-\frac{1}{2}} = \mathbb{E}_{t-1} \left[\frac{\partial \ell_t}{\partial f_t \partial f_t'} \right]^{-\frac{1}{2}}$.

↪ Harvey (2013) and Blasques et al. (2015) discuss the theoretical properties of score driven models;

↪ The model properly tracks skewness, if present!

MC exercise

Score update: information processing



Time-varying distribution: secular and cyclical

Each parameter consists of a permanent and a transitory components (Engle & Lee 1999):

$$\mu_{t+1} = \bar{\mu}_{t+1} + \tilde{\mu}_{t+1}$$
$$\bar{\mu}_{t+1} = \bar{\mu}_t + \kappa_{\bar{\mu}t} s_{\mu t}$$
$$\tilde{\mu}_{t+1} = \phi_{1,\tilde{\mu}} \tilde{\mu}_t + \phi_{2,\tilde{\mu}} \tilde{\mu}_{t-1} + \kappa_{\tilde{\mu}} s_{\mu t}$$

$$\ln(\sigma_{t+1}) = \bar{\gamma}_{t+1} + \tilde{\gamma}_{t+1}$$
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$$\varrho_{t+1} = \operatorname{atanh}(\bar{\delta}_{t+1} + \tilde{\delta}_{t+1})$$
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- X_t = NFCI or its 4 sub-indicators (Risk, Leverage, Nonfinancial Leverage and Credit).

Bayesian Estimation

Models are estimated with Bayesian methods:

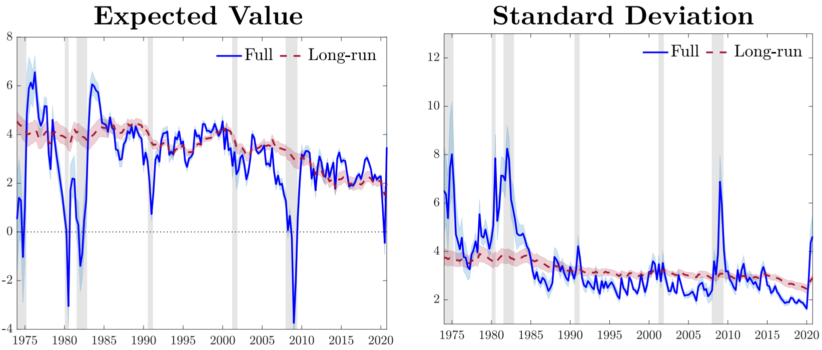
I) we impose (conservative) priors on the time variation of the parameters,
   - $\hookrightarrow$ Minnesota (persistence) and “Ridge” (predictor loadings) priors

II) we account for parameter uncertainty when producing forecasts
   - $\hookrightarrow$ Posteriors are obtained via Adaptive Metropolis-Hastings algorithm, augmented with rejection sampling. A-MH

We use data on US real GDP from 1972Q1 to 2020Q4, quarterly NFCI and the relative subcomponents. Data

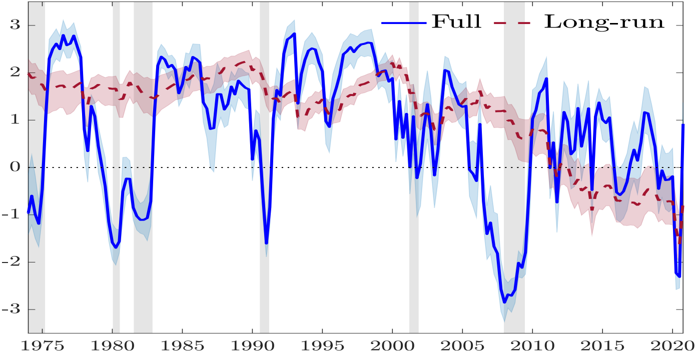
Results

Time-varying distribution: mean and variance



- Long-term growth slowdown at the turn of the century.
- Clear break in volatility in the mid ’80s - Great Moderation (GM).

Time-varying distribution: skewness



- The GM is associated with decreasing long-run skewness, turning negative after the Great Recession of 2008.
- Financial variables allow skewness to fall ahead of recessions.

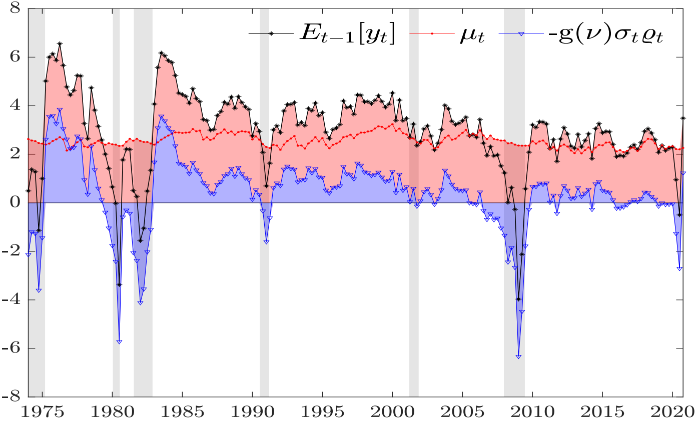
Expected growth decomposition

Higher order moments trigger a correction in the first moment so as to account for the asymmetry and variability of economic downturns:

$$\mathbb{E}[y_t] = \mu_t - \underbrace{\frac{4c(\nu)\nu}{\nu - 1}\sigma_t \varrho_t}_{g(\nu, \sigma_t, \varrho_t)}$$

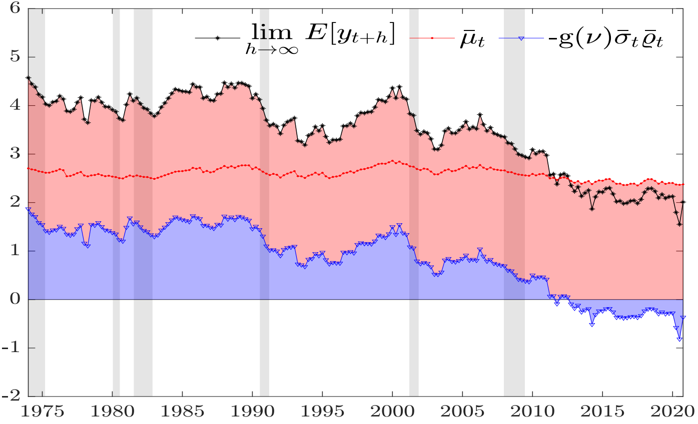
During economic expansions, expected growth is less affected by the higher order moments due to close-to-symmetric low-variance distributions.

Expected growth decomposition



- Cyclical variations are mainly driven by movements of the asymmetry.

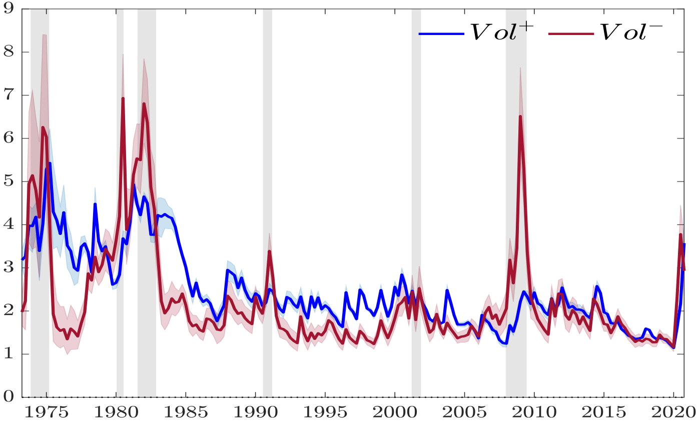
Expected growth decomposition in the long-run



- Increasing downside risk accounts for a large share of the long-run growth slowdown of the early 2000s.

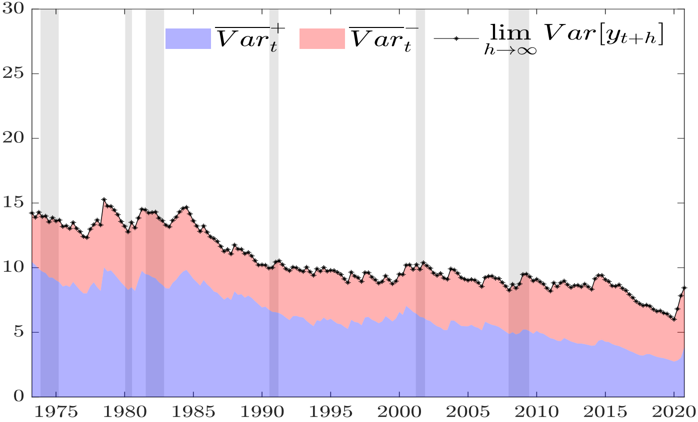
Upside and *Downside* volatility...

$$Vol^{+} = \sqrt{\frac{1-\varrho_t}{2} Var(y_t|Y_{t-1})}, \quad Vol^{-} = \sqrt{\frac{1+\varrho_t}{2} Var(y_t|Y_{t-1})}$$



- Countercyclicality of volatility is manly driven by downside volatility fluctuations.

...in the long-run



- The GM is associated with a fall in upside volatility.

Forecasting

Setting

- We produce forecasts for the period 1980Q1 to 2018Q4
  - $\hookrightarrow$ we use **real-time** GDP data
  - $\hookrightarrow$ 1- to 4-quarters-ahead, expanding window scheme
  - $\hookrightarrow$ $(h > 1)$-forecasts are obtained via *bootcast* Bootcast

- Forecasts are evaluated both on point (RMSFE) and density forecasts (logScore, CRPS and weighted CRPS, wQS, highlighting the left side of the distribution)

Comparison wrt Gaussian AR(2)-SV

	Skt	*Skt NFCI*	*Skt 4DFI*	*Skt*	*Skt NFCI*	*Skt 4DFI*
	One-quarter ahead					
	MSFE			**logS**		
Full	**0.842** (0.000)	**0.817** (0.000)	**0.812** (0.000)	**0.122** (0.000)	**0.140** (0.000)	**0.060** (0.084)
Post '00	**0.809** (0.000)	**0.804** (0.000)	**0.793** (0.000)	**0.181** (0.000)	**0.211** (0.000)	**0.167** (0.001)
Rec.	0.955 (0.315)	**0.822** (0.067)	**0.813** (0.067)	**0.349** (0.006)	**0.380** (0.007)	**0.270** (0.081)
	CRPS			**wQS**		
Full	**0.964** (0.047)	**0.941** (0.005)	**0.952** (0.025)	**0.960** (0.064)	**0.926** (0.006)	**0.926** (0.009)
Post '00	**0.934** (0.000)	**0.912** (0.000)	**0.918** (0.000)	**0.919** (0.000)	**0.894** (0.000)	**0.891** (0.002)
Rec.	0.962 (0.265)	0.934 (0.183)	0.928 (0.156)	0.948 (0.189)	0.914 (0.104)	**0.858** (0.025)
	One-year ahead					
	MSFE			**logS**		
Full	**0.720** (0.000)	**0.716** (0.002)	**0.694** (0.003)	**0.486** (0.000)	**0.585** (0.000)	**0.518** (0.001)
Post '00	**0.723** (0.000)	**0.699** (0.000)	**0.731** (0.004)	**0.814** (0.000)	**0.934** (0.000)	**0.895** (0.000)
Rec.	**0.574** (0.000)	**0.620** (0.030)	**0.545** (0.005)	**1.464** (0.000)	**1.572** (0.001)	**1.777** (0.001)
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Post '00	**0.846** (0.000)	**0.831** (0.000)	**0.831** (0.000)	**0.731** (0.000)	**0.709** (0.000)	**0.726** (0.001)
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Comparison wrt Adrian et al. (2019)

- Our model provides competitive forecasting advantages with respect to state-of-the-art models.

Forecast performance with respect to Adrian et al. (2019)

	One-quarter ahead				***One-year ahead***			
	MSFE	**logS**	**CRPS**	**wQS**	**MSFE**	**logS**	**CRPS**	**wQS**
Full	**0.890** (0.000)	**2.473** (0.000)	0.983 (0.221)	1.006 (0.599)	1.014 (0.561)	**0.571** (0.000)	0.989 (0.426)	1.026 (0.670)
Post '00	**0.837** (0.000)	**4.499** (0.000)	**0.920** (0.000)	**0.941** (0.006)	0.906 (0.133)	**0.394** (0.002)	**0.914** (0.073)	0.954 (0.269)
Rec.	1.110 (0.828)	**0.841** (0.000)	1.030 (0.689)	1.005 (0.534)	1.048 (0.581)	**1.387** (0.017)	0.900 (0.239)	0.943 (0.358)

Note: The table reports the average forecast metrics from the *Skt* -4DFI model relative to Adrian et al. (2019). We use ratios for the MSFE, CRSP and wQS, and differences for the logS. Ratios smaller than 1, and positive values of the log-score differences indicate that the *Skt* 4DFI model performs better than Adrian et al. (2019). The p-value for Diebold & Mariano (1995) test are in parentheses. Values in **bold** are significant at the 10% level.

Calibration test

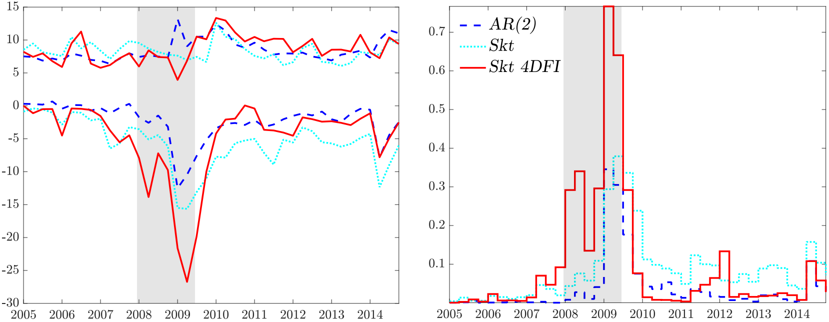
- Forecasts from our model turn out to be well calibrated, contrary to the benchmark models.

Density calibration tests

	AR(2)	*ABG*	*Skt 4DFI*	*AR(2)*	*ABG*	*Skt 4DFI*
	One-quarter ahead			***One-year ahead***		
Dist.	**2.102**	**1.925**	0.883	**4.865**	**2.306**	1.162
Left tail	**1.074**	**1.166**	0.501	**4.757**	**2.306**	1.162

Note: The table reports the test statistics for the Rossi & Sekhposyan (2019) tests, based on the Kolmogorov-Smirnov type tests. The left tail score is computed over the support [0, 0.25]. Values in **bold** indicate the rejection of the null hypothesis of correct specification of the density forecast at the 10% confidence level. Critical values are obtained by 1000 bootstrap simulations. Gray shaded cells indicate the lowest value of the statistic.

Downside risk

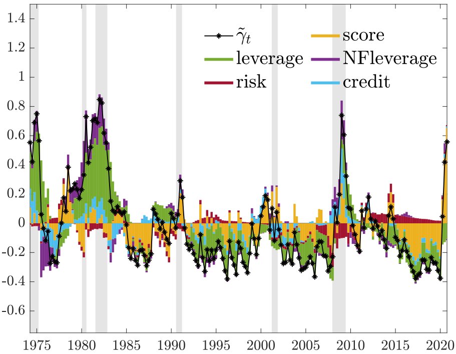


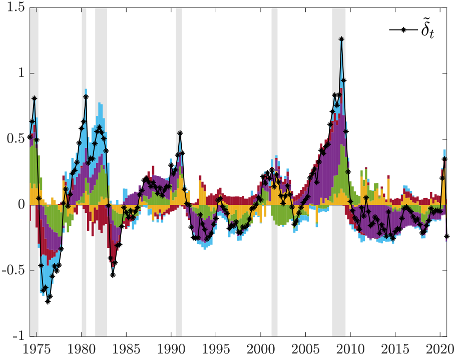
ES and EL $\quad$ $P(Rec_t^{t+4}|Y_t)$

- Significant improvements in downside risk predictions, especially at the year horizon (as measured by Fissler et al. (2016), Taylor (2019) and Giacomini & Komunjer (2005) loss functions).
- Gains in predicting recession (assessed using Brier score)

Financial predictors

How important are financial predictors?





- Financial predictors play an important role in driving the time-varying shape of GDP distribution
- The scale and shape of the distribution are affected by different financial indicators.

Can we exploit more info?

"Shrink-then-sparsify"

We condition the *tvp* on the full set of the contributions of 105 financial indicators to the NFCI, and we set to zero the loadings of non-informative variables

List

	Shrink
Carvalho et al. (2010)	$c^j \sim \mathcal{N}(0, \lambda^j \tau)$
	$\lambda^j \sim HC^+(0,1), \quad \tau \sim HC^+(0,1)$
	Sparsify
Ray & Bhattacharya (2018)	$m^j = \|\hat{c}^j\|^{-2}$
	$c^{j*} = sgn(\hat{c}^j)\|\|X^j\|\|^{-2} \max\left\{\|\hat{c}^j\| \cdot \|\|X^j\|\|^2 - m^j\right\}_+$

StS model's forecast metrics

- Large financial information provides to be useful, specifically for short-term prediction.

Big Data forecast performance

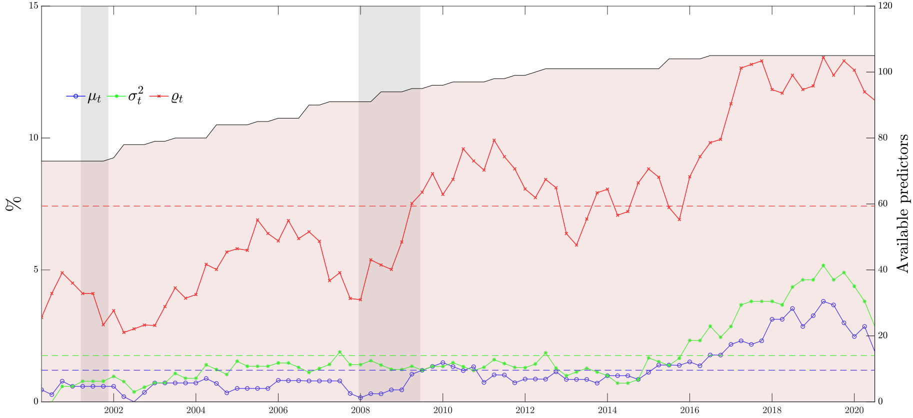
	One-quarter ahead				***One-year ahead***			
	MSFE	**logS**	**CRPS**	**wQS**	**MSFE**	**logS**	**CRPS**	**wQS**
Full	**0.185** (0.000)	0.223 (0.163)	**0.655** (0.000)	**0.657** (0.000)	0.434 (0.112)	0.222 (0.562)	0.833 (0.259)	0.776 (0.250)
Pre Pandemic	**1.290** (0.087)	−0.108 (0.351)	1.109 (0.286)	**1.191** (0.071)	1.157 (0.637)	−0.065 (0.785)	1.051 (0.736)	1.083 (0.706)
Rec.	**0.408** (0.003)	0.357 (0.228)	**0.679** (0.035)	**0.708** (0.067)	0.649 (0.171)	0.664 (0.395)	0.591 (0.143)	0.449 (0.102)

Note: The table reports the average forecast metrics from the big data model relative to *Skt* 4DFI. We use ratios for the MSFE, CRSP and wQS, and differences for the logS. Ratios smaller than 1, and positive values of the log-score differences indicate that the big data model performs better than *Skt* 4DFI. The p-value for Diebold & Mariano (1995) test are in parentheses. Values in **bold** are significant at the 10% level.

TVP predictability

Credit and **leverage** indicators receive the least shrinkage.

List | List - GFC



Conclusions

- The distribution of GDP growth exhibits significant time variation in its first tree moments;
  - ↪ We introduce a flexible parametric approach to characterize the full conditional distribution.
- Real economic growth features procyclical skewness
  - ↪ decreasing long-run skew over GM period accounts for large share of growth slowdown.
- Financial variables anticipate increasing downside risk to the economy
  - ↪ improved density forecasts, especially around recessions.
- Leverage and Credit indicators drive asymmetry dynamics
  - ↪ Building-up of household leverage (Mian & Sufi 2010, Jordà et al. 2013)

Modeling and Forecasting Macroeconomic Downside Risk

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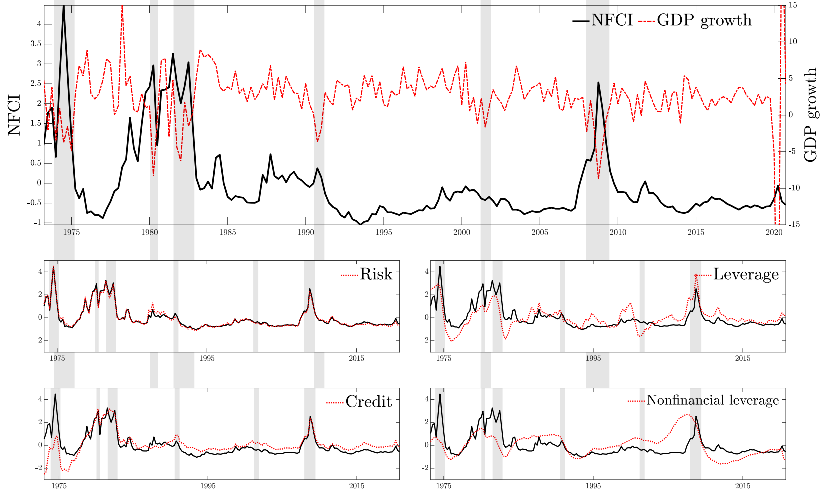
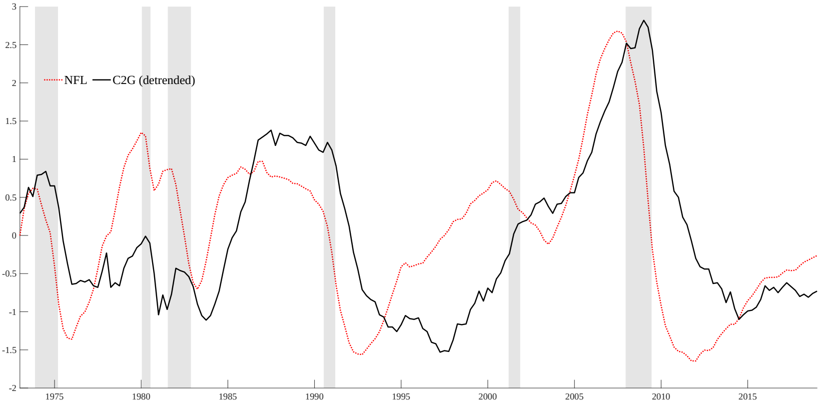
The views expressed in this presentation are those of the authors and do not necessarily reflect the views of the Bank of Italy. Any errors and omissions are the sole responsibility of the authors.

Data


NFCI
GDP growth
Risk
Leverage
Credit
Nonfinancial leverage

Nonfinancial leverage



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Adaptive Metropolis-Hastings

Given the vector of static parameters θ:

—MH steps—	
Draw:	$\theta^* = \theta^{j-1} + \epsilon,\ \epsilon \sim \mathcal{N}(0, \Sigma_H)$
Accept:	$\theta^j = \theta^*$ with probability $p = \min\left[1, \frac{f(\theta^j)}{f(\theta^{j-1})}\right]$
—Adaptive steps—	
Rescale:	$\sigma_s = \sigma_s r(\tilde{\alpha}^s)$, every s draws
Reestimate:	$\Sigma_H = \frac{\tilde{K}}{\sqrt{H-1}}$, every U draws

where $r(\tilde{\alpha}^s)$ is an arbitrary function of the local acceptance rate $\tilde{\alpha}^s$ to target a 30% acceptance rate.
We set $s = 100$, $U = 750$ and $H = 1000$.

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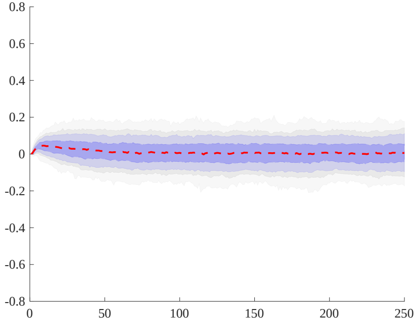
Simulation Exercise

Would the model find any skewness when there is no skewness in the data?



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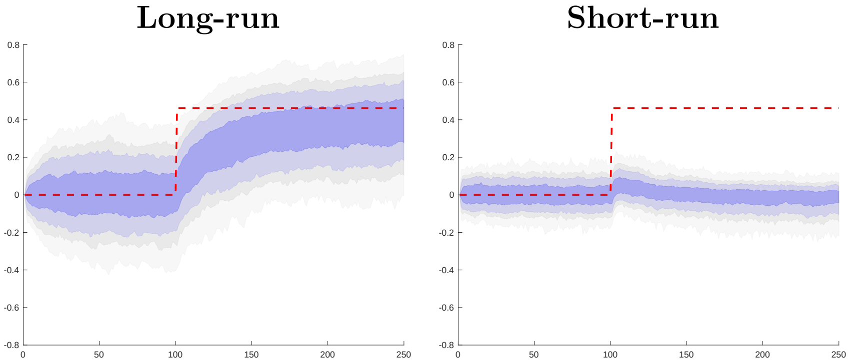
Simulation Exercise

How does the model handle sudden structural breaks?



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Multi-steps forecast

We forecast longer horizons using the *Bootcasting* approach of Koopman et al. (2018).

Given $\mathbf{s}_t \overset{iid}{\sim} (0, 1)$, we simulate future scores:

$$\mathbf{s}_{T+h} = \mathcal{I}_{T|T-1}^{-\frac{1}{2}} \underbrace{\mathcal{I}_{j|j-1}^{-\frac{1}{2}} \nabla_j}_{\mathbf{s}_j},$$

$$\mathbf{s}_{T+h+1} = \mathcal{I}_{T|T-1}^{-\frac{1}{2}} \mathbf{s}_{j+1}$$

where $j \sim U[h+1, T-h]$.

GDP forecasts are then obtained as:

$$y_{T+h|T} \sim skt_{\eta}(\mathbf{f}_{T+h}(\mathbf{s}_{T+h-1}))$$

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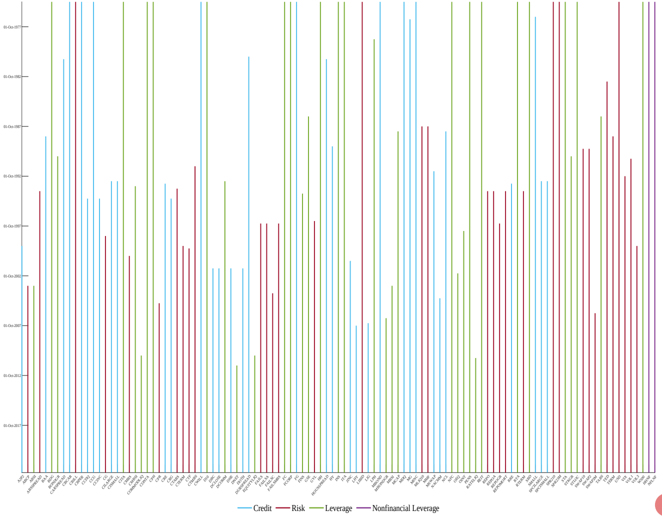
NFCI subindices



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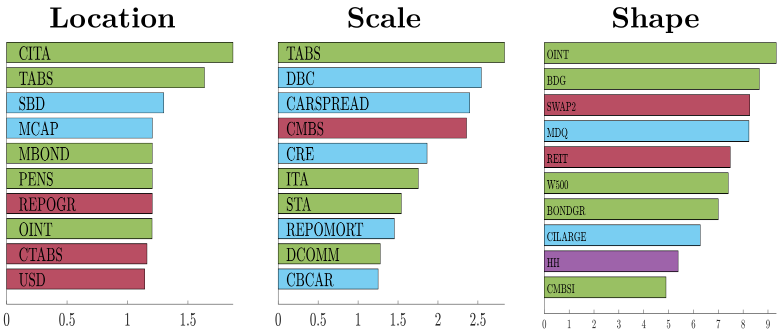
Shortlist: Top 10



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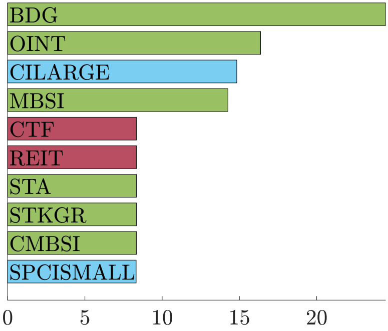
GFC Shortlist: Top 10 - ϱ_t



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