Forecasting Macroeconomic Tail Risk in Real Time: Do Textual Data Add Value?

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Motivation

- Quantile forecasts of macroeconomic time series allow for a quantile-specific predictive relationship between the target series and the covariates.

- The tails are associated with phases of high economic interest.

- The literature on macroeconomic forecasting has paid increasing attention to now- and forecasts of quantiles

  (see, e.g., Manzan, 2015; Korobilis, 2017; Adrian, Boyarchenko, and Giannone, 2019; Carriero, Clark, and Marcellino, 2020; Adams, Adrian, Boyarchenko, and Giannone, 2021; Clark, Huber, Koop, Marcellino, and Pfarrhofer, 2022; Prüser and Huber, 2023).

Motivation

- Another recent development in macroeconomic forecasting is the use of textual data.
- Textual predictors provide timely information that may embed complementary signals to (hard) economic indicators

  (see e.g., Larsen and Thorsrud, 2019; Bybee, Kelly, Manela, and Xiu, 2021; Ellingsen, Larsen, and Thorsrud, 2022).
- Most studies that use textual predictors for macroeconomic time series forecasts analyze only point forecasts.

What we do

- We explore the role of textual predictors for quantile now- and one-step-ahead forecasts.

- Linear and non-linear models:
  - Bayesian quantile regressions with different shrinkage priors
  - Gaussian Process Regressions
  - QR forests.

- Four target variables:
  - Employment
  - Inflation
  - Production
  - Consumer sentiment.

Bayesian quantile regressions

- The Bayesian QR can be stated as:

$$y_{t+h} = \boldsymbol{x}_t \boldsymbol{\beta}_\tau + \varepsilon_{\tau,t+h}.$$

- The shrinkage priors can be written in the general form:

$$\boldsymbol{\beta}_\tau | \psi_{\tau_1}, \ldots, \psi_{\tau_K}, \lambda_\tau \sim \prod_{j=1}^{K} \mathcal{N}\left(0, \psi_{\tau j} \lambda_\tau\right), \ \psi_{\tau j} \sim u, \quad \lambda_\tau \sim \pi.$$

  - Ridge: $\psi_{\tau j} = 1 \quad \forall \tau, j$ and $\lambda_\tau \sim \mathcal{IG}\left(0, 0\right)$
  - Horseshoe: $\sqrt{\psi_{\tau j}} \sim \mathcal{C}^+\left(0, 1\right)$ and $\sqrt{\lambda_\tau} \sim \mathcal{C}^+\left(0, 1\right)$
  - Lasso: $\psi_{\tau j} \sim \mathcal{G}\left(1, \lambda_\tau\right)$ and $\lambda_\tau \sim \mathcal{G}\left(0, 0\right)$.

Gaussian Process Regression

- Gaussian Process Regression is a non-parametric Bayesian method that elicits a process prior on the function $g_\tau\left(\mathbf{x}_t\right)$:

$$g_\tau\left(\mathbf{x}_t\right) \sim \mathcal{GP}\left(\mu_\tau\left(\mathbf{x}_t\right), \mathcal{K}\left(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}}\right)\right),$$

- We set the mean function $\mu_\tau\left(\mathbf{x}_t\right)$ to zero.

- The kernel function $\mathcal{K}\left(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}}^{'}\right)$ describes the relationship between $\mathbf{x}_t$ and $\mathbf{x}_{\mathrm{t}}$, for t, $\mathrm{t} = 1, \ldots, T$.

- We choose a squared exponential kernel:

$$\mathcal{K}\left(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}}\right) = w_1 \times e^{-\frac{w_2}{2}\left\|\mathbf{x}_t - \mathbf{x}_{\mathrm{t}}\right\|^2}.$$

QR forests

- QR forests is a non-parametric frequentist method that performs conditional quantile estimation based on an ensemble of trees (Meinshausen, 2006).
- The conditional distribution function y, given $X = x$, is

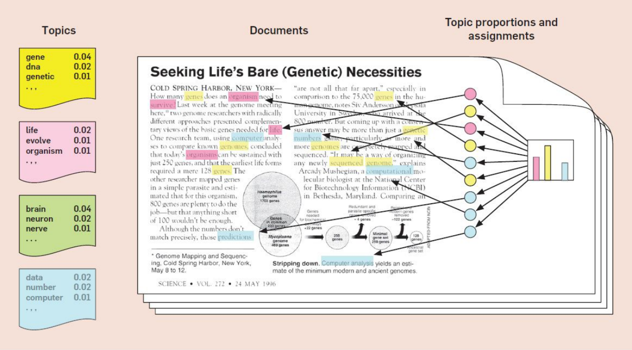
$$F(y|X=x) = P(Y \leq y|X=x) = \mathbb{E}\left(\mathbb{1}_{\{Y \leq y\}}|X=x\right).$$

- $\mathbb{E}\left(\mathbb{1}_{\{Y \leq y\}}|X=x\right)$ is approximated by the weighted mean over the observations $\mathbb{1}_{\{Y \leq y\}}$,

$$\widehat{F}(y|X=x) = \sum_{i=1}^{n} w_i(x)\, \mathbb{1}_{\{Y \leq y\}},$$

where the weights $w_i(x)$ are computed over the collection of trees.

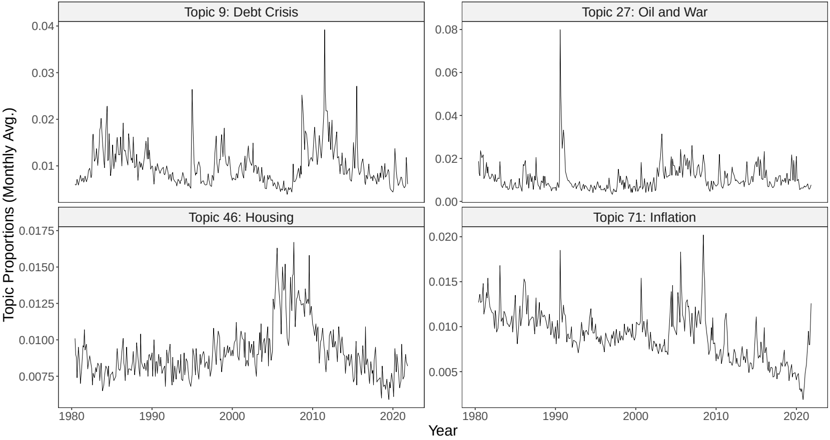
Textual predictors from topic models



Source: Blei, D.M. (2012). Probabilistic Topic Models.

- ♢ Correlated Topic Model with 793,013 newspaper articles from *The New York Times* and *The Washington Post*.
- ♢ 80 topic proportions (attention measures) as textual predictors.

Examples of topic proportions



Examples of estimated topic proportions (monthly averages).

Forecasting setup

- We consider three sets of predictive variables:
  - FRED-MD predictors only
    (vintage data, McCracken and Ng (2016))
  - Textual predictors only
  - FRED-MD predictors & textual predictors.

  In each setting we include 12 lags of the target variable.

- For nowcasts of month t, we use
  - macro predictors from $t-1$, released in t
  - financial and textual predictors from t.

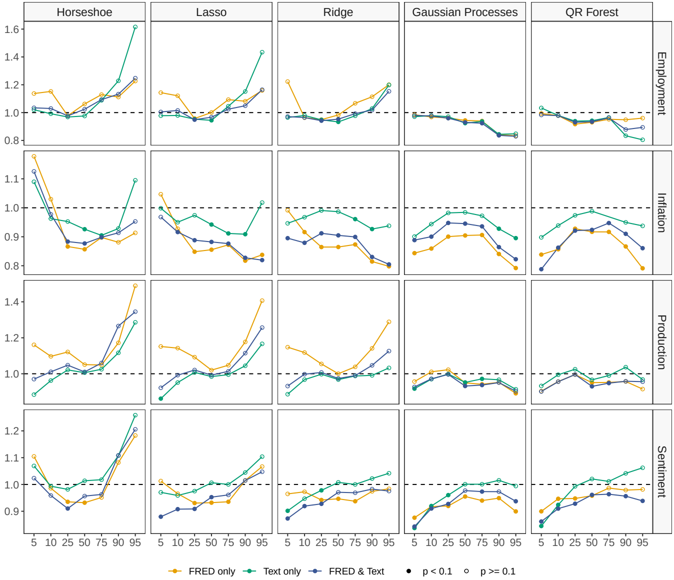
Forecasting setup

- Our estimation sample starts in 1980:06.
- We run recursive estimations based on an expanding window.
- Our evaluation period ranges from 1999:10 to 2021:12.
- We evaluate our forecasting models with the quantile score (QS):

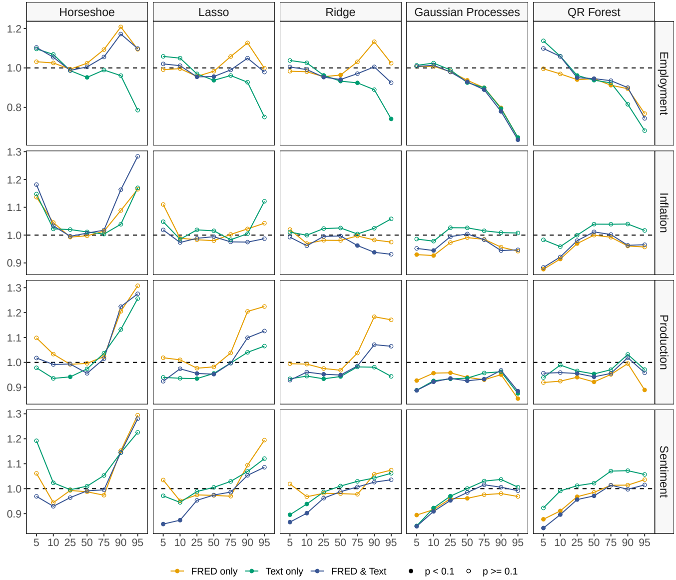
$$QS_{\tau,t+h} = (y_{t+h} - Q_{\tau,t+h}) \left(\tau - 1_{\{y_{t+h} \leq Q_{\tau,t+h}\}} \right).$$

- τ: $\tau = 5\%, 10\%, 25\%, 50\%, 75\%, 90\%, 95\%$.

Nowcasts: QS relative to AR(1)



One-step-ahead forecasts: QS relative to AR(1)



Main results

- Addition of textual predictors often leads to lower quantile score, in particular
  - in the tails,
  - for the linear forecasting models.
- Ridge prevails over Horseshoe and Lasso.
- Gaussian Process Regressions have a slight edge over QR forests.
- Quantile scores are mainly U-shaped for linear models and hump-shaped for non-linear models.

Which predictors determine the quantile forecasts?

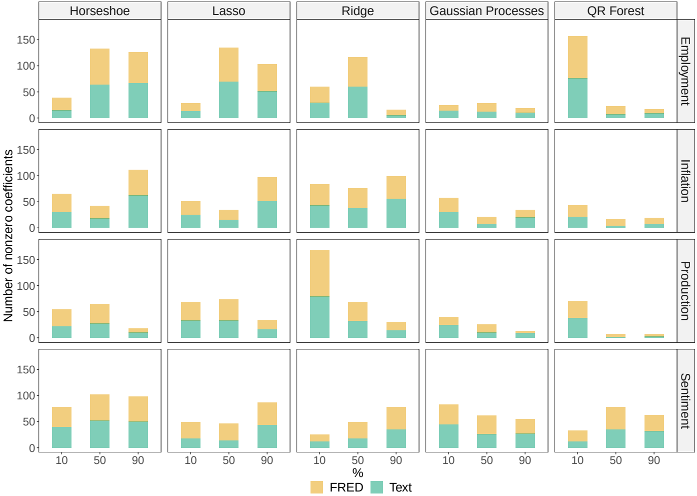
- We wish to ensure comparability for predictor importance across heterogeneous forecasting methods.

- We approximate the quantile predictions $Q_{\tau,t+h}$ with a Lasso-type regression (Woody, Carvalho, and Murray, 2021):

$$\boldsymbol{\beta}_\tau^* = \arg\min_{\boldsymbol{\beta}_\tau} \sum_{t=t_0}^{T-h} \left(Q_{\tau,t+h} - \boldsymbol{\beta}_\tau' \mathbf{x}_t\right)^2 + \lambda \sum_{j=1}^{K} |\beta_{\tau,j}| \,.$$

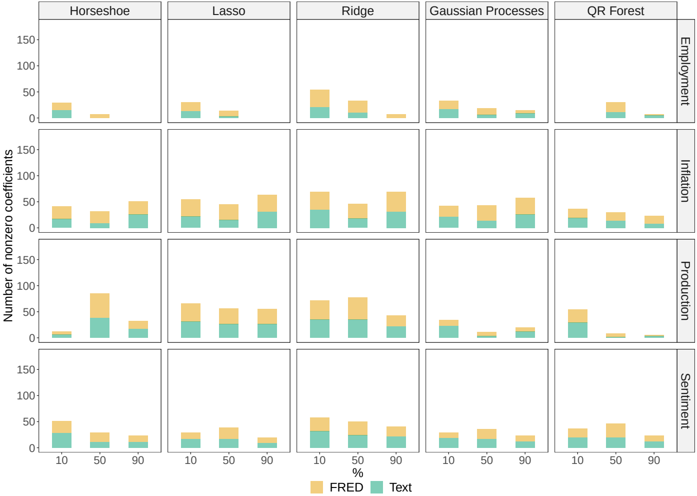
Nowcasts: Variable importance

$\tau = 10\%$



One-step-ahead forecasts: Variable importance

$\tau = 10\%$



Key takeaways

- We have examined the incremental predictive power of textual predictors for quantile forecasts.
- We have considered forecasting models that feature linear and non-linear (quantile-specific) predictive relationships.
- Non-linear predictive relationships achieved the best forecasting results.
- Overall, combinations of FRED and textual predictors produced the most accurate forecasts, especially in the left tail.

Nowcasts: Variable importance I

$\tau = 10\%$

One-step-ahead forecasts: Variable importance I

$\tau = 10\%$

References I

Adams, P. A., T. Adrian, N. Boyarchenko, and D. Giannone (2021): "Forecasting macroeconomic risks," *International Journal of Forecasting*, 37(3), 1173–1191.

Adrian, T., N. Boyarchenko, and D. Giannone (2019): "Vulnerable growth," *American Economic Review*, 109(4), 1263–89.

Bybee, L., B. T. Kelly, A. Manela, and D. Xiu (2021): "The structure of economic news," Discussion paper, National Bureau of Economic Research.

Carriero, A., T. E. Clark, and M. G. Marcellino (2020): "Nowcasting tail risks to economic activity with many indicators," Discussion paper, FRB of Cleveland Working Paper No. 20-13R2.

References II

Clark, T. E., F. Huber, G. Koop, M. Marcellino, and M. Pfarrhofer (2022): "Tail forecasting with multivariate Bayesian additive regression trees," *International Economic Review*.

Ellingsen, J., V. H. Larsen, and L. A. Thorsrud (2022): "News media versus FRED-MD for macroeconomic forecasting," *Journal of Applied Econometrics*, 37(1), 63–81.

Korobilis, D. (2017): "Quantile regression forecasts of inflation under model uncertainty," *International Journal of Forecasting*, 33(1), 11–20.

Larsen, V. H., and L. A. Thorsrud (2019): "The value of news for economic developments," *Journal of Econometrics*, 210(1), 203–218.

References III

Manzan, S. (2015): "Forecasting the distribution of economic variables in a data-rich environment," *Journal of Business & Economic Statistics*, 33(1), 144–164.

McCracken, M. W., and S. Ng (2016): "FRED-MD: A monthly database for macroeconomic research," *Journal of Business & Economic Statistics*, 34(4), 574–589.

Meinshausen, N. (2006): "Quantile regression forests.," *Journal of Machine Learning Research*, 7(6).

Prüser, J., and F. Huber (2023): "Nonlinearities in Macroeconomic Tail Risk through the Lens of Big Data Quantile Regressions," *arXiv preprint arXiv:2301.13604*.

Woody, S., C. M. Carvalho, and J. S. Murray (2021): "Model interpretation through lower-dimensional posterior summarization," *Journal of Computational and Graphical Statistics*, 30(1), 144–161.