

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:

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

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

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

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

Gaussian Process Regression

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

$$g_{\tau}(\mathbf{x}_t) \sim \mathcal{GP}(\mu_{\tau}(\mathbf{x}_t), \mathcal{K}(\mathbf{x}_t, \mathbf{x}_t)),$$

- ◇ We set the mean function $\mu_{\tau}(\mathbf{x}_t)$ to zero.
- ◇ The kernel function $\mathcal{K}(\mathbf{x}_t, \mathbf{x}_t')$ describes the relationship between \mathbf{x}_t and \mathbf{x}_t' , for $t, t' = 1, \dots, T$.
- ◇ We choose a squared exponential kernel:

$$\mathcal{K}(\mathbf{x}_t, \mathbf{x}_t') = w_1 \times e^{-\frac{w_2}{2} \|\mathbf{x}_t - \mathbf{x}_t'\|^2}.$$

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

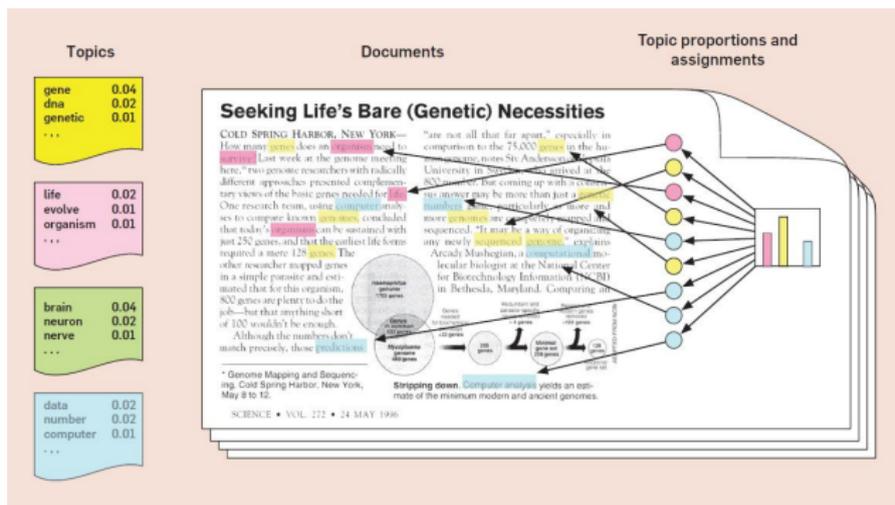
$$F(y|X = x) = P(Y \leq y|X = x) = \mathbb{E} \left(\mathbb{1}_{\{Y \leq y\}} | X = x \right).$$

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

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

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

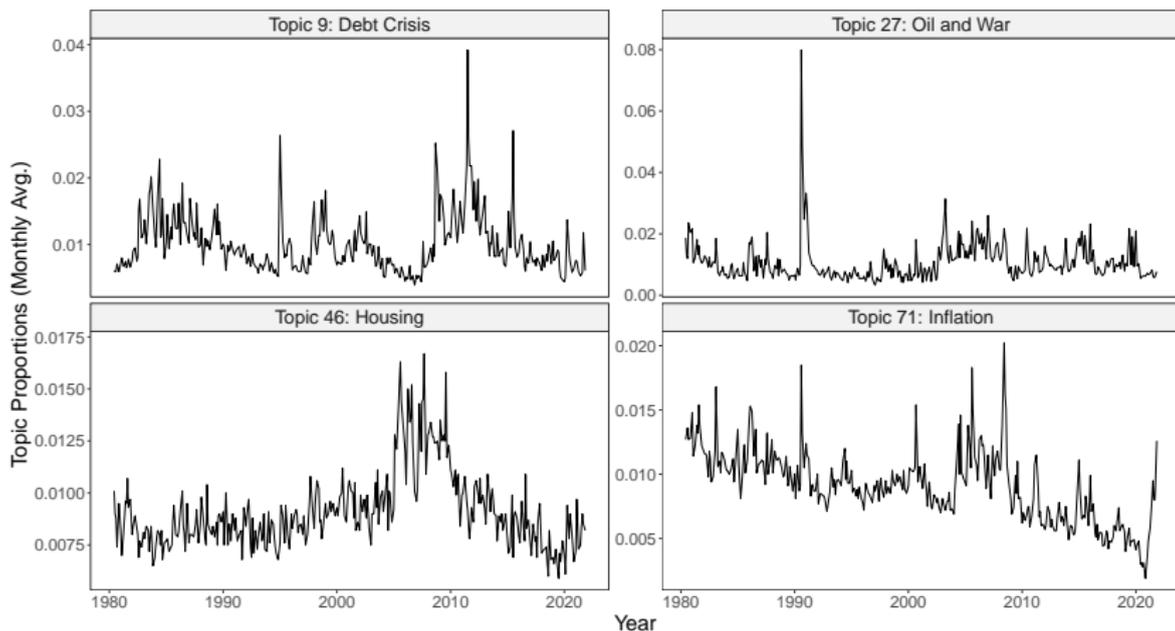
Textual predictors from topic models



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 .

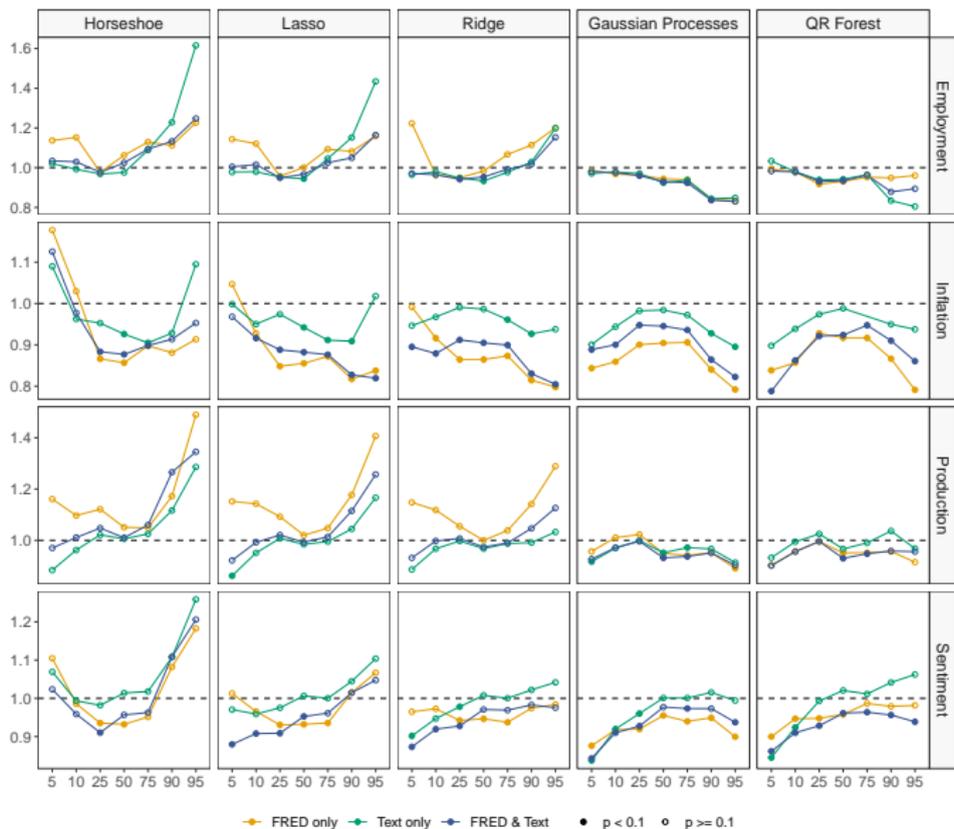
Forecasting setup

- ◇ 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):

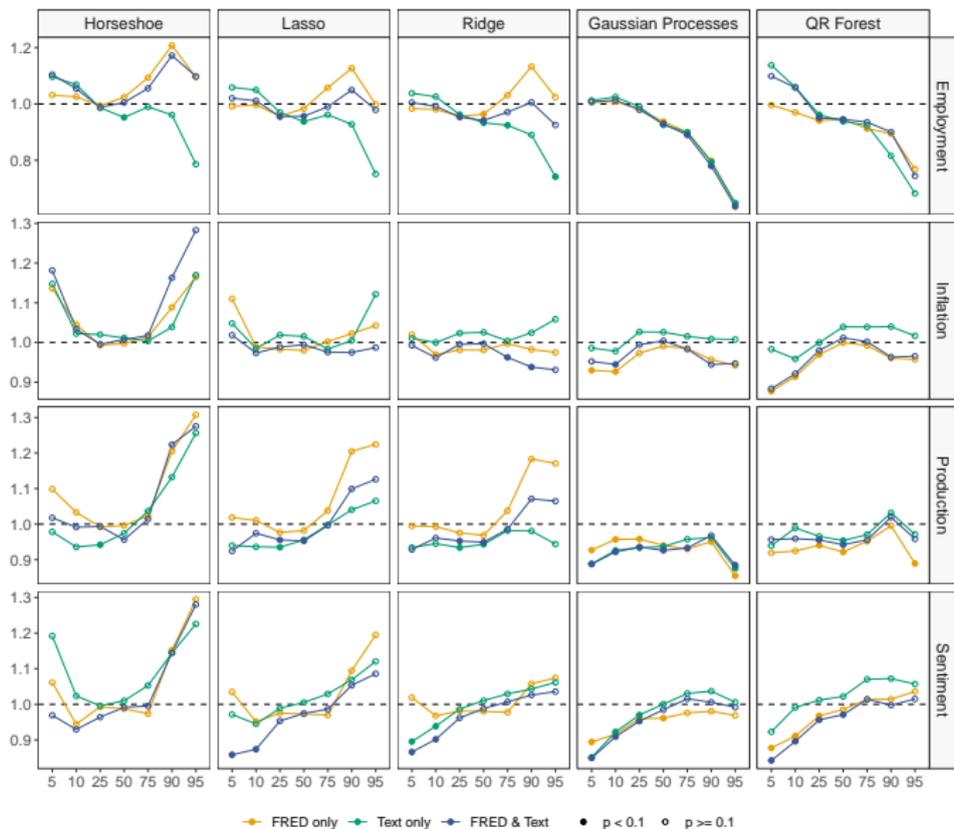
$$QS_{\tau,t+h} = (y_{t+h} - Q_{\tau,t+h}) \left(\tau - 1_{\{y_{t+h} \leq Q_{\tau,t+h}\}} \right).$$

- ◇ 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.

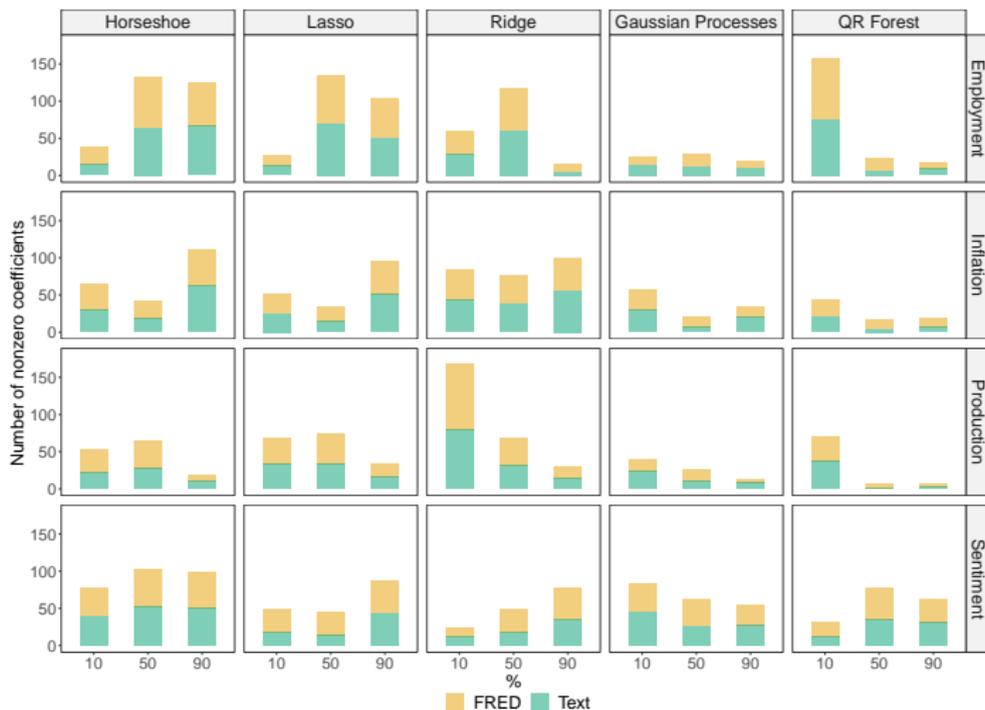
Which predictors determine the quantile forecasts?

- ◇ 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):

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

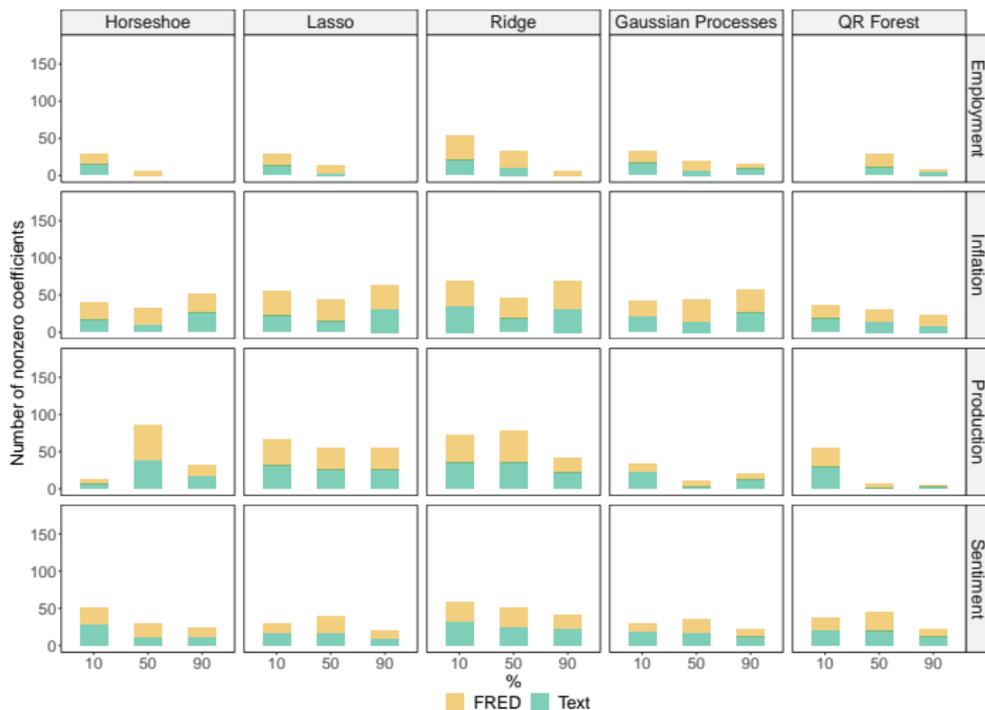
Nowcasts: Variable importance

$\tau = 10\%$



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

$\tau = 10\%$



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