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

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June 1, 2023

We examine the incremental value of news-based data relative to the *FRED-MD* economic indicators for quantile predictions (now- and forecasts) of employment, output, inflation and consumer sentiment. Our results suggest that news data contain valuable information not captured by economic indicators, particularly for left-tail forecasts. Methods that capture quantile-specific non-linearities produce superior forecasts relative to methods that feature linear predictive relationships. However, adding news-based data substantially increases the performance of quantile-specific linear models, especially in the left tail. Variable importance analyses reveal that left tail predictions are determined by both economic and textual indicators, with the latter having the most pronounced impact on consumer sentiment.

KEYWORDS: Quantile Regression, Textual data, Topic models, Quantile Regression Forests, Gaussian process, Global-local priors

JEL: C53, C55, E27, E37

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[*]We thank Ignacio Moreira for excellent research assistance. We further gratefully acknowledge the support of the German Research Foundation (project ID 468814087 and project ID 468715873).

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1 Introduction

Tail risk forecasts of macroeconomic time series provide a more nuanced picture than point forecasts as the former allow for asymmetric links, meaning that the predictive relationship between the target variable and the covariates can vary across quantiles. The focus here is typically on the tails, which are associated with phases of high interest such as economic booms and busts. This is why 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).

Another recent development in macroeconomic forecasting is the use of textual data, which 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). While most studies analyze the benefits of textual predictors for macroeconomic point forecasts, the role of textual predictors for tail forecasting is largely unexplored.[1] In this paper, we study the benefits of such data for forecasting macroeconomic tail risk in real time. In addition, we explore whether the impact of textual predictors differs across forecasting models that feature linear or non-linear predictive relationships.

Our focus is on monthly tail risk (now- and one-step-ahead) forecasts of employment, industrial production, inflation and consumer sentiment between 1999:10 and 2021:12. As data revisions are an important issue in out-of-sample (OOS) macroeconomic forecasting, we use real-time vintages of economic predictors contained in the widely used McCracken and Ng (2016) *FRED-MD* database. In addition, we use a large set of news attention measures (topic proportions) as predictors, which we obtain from the Correlated Topic Model (CTM). The CTM is an unsupervised machine learning algorithm that estimates our news predictors on almost 800,000 newspaper articles from *The New York Times*

[1] An exception is Barbaglia, Consoli, and Manzan (2022) who extend their setting to quantile forecasts and find that sentiment predictors provide explanatory power for the tails.

and *The Washington Post*.[2] The most frequent words within each topic (word cluster) characterize its theme, and the proportion indicates the degree of media coverage of a certain topic at a given point in time. For example, during times of rising energy and consumer prices, a topic about inflation is supposed to gain importance, reflected by a rising topic proportion. The dynamics of topic proportions might further contain signals not captured by traditional economic data. Can such signals be exploited to improve tail risk forecasts? To address this question, we use different sets of predictors: economic predictors only, textual predictors only, and both types of predictors.

Two key insights guided our choice of forecasting models. First, mechanisms to prevent overfitting are necessary for OOS forecasting in high-dimensional settings like ours. We thus use three Bayesian quantile regressions (QR) with different shrinkage priors which assume a linear relationship between the quantile-specific target variables and the covariates. Second, recent studies point to the importance of capturing non-linear predictive relationships. For example, Goulet Coulombe, Leroux, Stevanovic, and Surprenant (2022) consider capturing non-linearities as the "true game changer" of machine learning methods for macroeconomic forecasting, which is corroborated by Medeiros, Vasconcelos, Veiga, and Zilberman (2021) and Clark, Huber, Koop, Marcellino, and Pfarrhofer (2022), finding strong empirical support for tree-based methods. To capture non-linear relationships between the quantile-specific target variables and the covariates, we use non-parametric Bayesian Gaussian Process Regressions (Williams and Rasmussen, 2006) and QR Forests (Meinshausen, 2006). Entertaining both forecasting methods that feature linear and non-linear predictive relationships enables us to evaluate

[2] Economic studies have predominantly relied on latent Dirichlet allocation (LDA) by Blei, Ng, and Jordan (2003) to extract news-based predictors. These predictors have then been used, for instance, to investigate the value of news data for modeling macroeconomic dynamics (Larsen and Thorsrud, 2019; Bybee, Kelly, Manela, and Xiu, 2021), to construct a daily business cycle index (Thorsrud, 2020), to predict US macroeconomic variables (Ellingsen, Larsen, and Thorsrud, 2022), and to nowcast US GDP Babii, Ghysels, and Striaukas (2021). LDA, however, has some theoretical and computational drawbacks, which is why we apply the advantageous correlated topic model (CTM) by Blei and Lafferty (2007). The CTM and further extensions have been used to produce news attention measures which have then been used, for example, to analyze news coverage of China (Roberts, Stewart, and Airoldi, 2016), to investigate the impact of presidential tax speeches on economic activity (Dybowski and Adämmer, 2018), to forecast the equity premium (Adämmer and Schüssler, 2020), and to analyze European Central Bank communication (Dybowski and Kempa, 2020; Bohl, Kanelis, and Siklos, 2023).

the empirical differences between the model classes.

Our results corroborate empirical evidence that textual data contain valuable incremental information, being particularly useful for predicting events in the left tail of the distribution and less so in its center. This finding is consistent with a narrative that timely news signals are most helpful in extreme economic situations. Our variable importance analyses show that both economic and textual indicators are used for left tail predictions. Importantly, combining text and FRED data can yield sizable gains in forecast accuracy and is never much worse than using FRED data only. Moreover, methods which can capture non-linearities produce better now- and forecasts than those which cannot. However, incorporating textual predictors into models that assume a quantile-specific linear predictive relationship leads to competitive predictions, especially for the left tail. We finally observe substantial forecast accuracy gains for consumer sentiment when using textual data, which is consistent with the notion that news data are important in forming household expectations (Larsen, Thorsrud, and Zhulanova, 2021).

The paper proceeds as follows. Section 2 lays out our methodology. Section 3 outlines our forecasting setup, introduces our predictors, and presents our forecast results. Section 4 concludes. Additional material is relegated in the appendix.

2 Methodology

2.1 Forecasting methods

2.1.1 Bayesian Quantile Regression

In settings with many regressors, Bayesian shrinkage alleviates overfitting and thus noisy forecasts. Recently, Carriero, Clark, and Marcellino (2022) showed the importance of using shrinkage for QR in empirical macroeconomics. For Bayesian estimation, we use the mixture representation established by Yu and Moyeed (2001). For a given variable y of interest that is to be predicted for quantile τ at horizon h, the Bayesian QR can be stated as

$$y_{t+h} = \mathbf{x}_t \beta_\tau + \varepsilon_{\tau,t+h}, \tag{1}$$

where $\{x_t\}_{t=1}^{T-h}$ is a K-dimensional vector of predictors, and K denotes the set of predictors that depends on the setting (*FRED* predictors only, textual predictors only, or *FRED* and textual predictors together). Let β_τ denote a K-dimensional vector of quantile-specific regression coefficients, and $\varepsilon_{\tau,t+h}$ has a mixture representation. The shocks are assumed to follow an asymmetric Laplace distribution (Yu and Moyeed, 2001).

Using the mixture representation, we can rewrite the QR model (1) as

$$y_{t+h} = \mathbf{x}_t \beta_\tau + \theta_\tau z_{\tau,t+h} + \kappa_\tau \sqrt{\sigma_{\tau,h} z_{\tau,t+h}} u_{t+h}, \tag{2}$$

where $z_{\tau,t+h}$ is exponentially distributed with scale parameter $\sigma_{\tau,h}$; θ_τ and κ_τ are quantile-specific fixed parameters, u_{t+h} is i.i.d. standard normal.

Posterior inference requires specifying a likelihood and eliciting priors for the coefficients. As Markov Chain Monte Carlo estimation is slow in high dimensions, we use fast variational Bayes approximations for posterior inference. In the interest of brevity we do not give full details of the estimation, but note that, by introducing auxiliary latent variables, the likelihood is conditionally Gaussian and the errors are conditionally heteroskedastic. The shrinkage priors we consider fall into the class of global-local shrinkage priors, where the prior variance comprises one global term pertaining to all coefficients and another coefficient-specific term. The three shrinkage priors we use can be written in the general form

$$\beta_\tau | \psi_{\tau_1}, \ldots, \psi_{\tau_K}, \lambda_\tau \sim \prod_{j=1}^{K} \mathcal{N}\left(0, \psi_{\tau j} \lambda_\tau\right), \ \psi_{\tau j} \sim u, \quad \lambda_\tau \sim \pi, \tag{3}$$

where λ_τ denotes a quantile-specific global shrinkage parameter and $\psi_{\tau j}$ are quantile-specific local scaling parameters that control the coefficient-specific shrinkage intensities. Different shrinkage priors are generated by choosing different mixing densities via the functions u and π. We consider the three following shrinkage priors that are popular choices in macroeconomic forecasting; see, e.g., Huber and Feldkircher (2019), Cross, Hou, and Poon (2020), and Prüser (2023):

- Ridge: The Ridge prior collapses to a purely global shrinkage prior since all local scaling parameters are set equal to 1. The global shrinkage parameter follows an inverse Gamma distribution. Formally, we thus have: $\psi_{\tau j} = 1 \quad \forall \tau, j$ and $\lambda_\tau \sim \mathcal{IG}(e_0, e_1)$. We choose the hyperparameters $e_0 = e_1 = 0$, thus shrinking all coefficients towards zero in the same vein. Overall, the Ridge prior offers a comparatively low degree of flexibility for variable-specific deviations from the global shrinkage pattern. This prior is supposed to work well when many predictors are relevant, being consistent with a dense representation of the prediction problem.

- Horseshoe: In contrast to the Ridge prior, the Horseshoe prior (Carvalho, Polson, and Scott, 2010) offers variable-specific shrinkage. The Horseshoe sets u and π to half-Cauchy distributions, respectively: $\sqrt{\psi_{\tau j}} \sim \mathcal{C}^+(0, 1)$ and $\sqrt{\lambda_\tau} \sim \mathcal{C}^+(0, 1)$. An advantage of the Horseshoe prior is that it does not require the researcher to elicit any tuning parameters. The Horseshoe prior has been shown to have excellent posterior contraction properties, see, e.g., Ghosh, Tang, Ghosh, and Chakrabarti (2016). The Horseshoe prior spikes at zero and has fat tails. Hence, it is supposed to shrink small coefficients of unimportant predictors to zero, but (in relative terms) large coefficients of the informative predictors are not shrunk much. Accordingly, the Horseshoe prior should work well when only a small number out of the pool of predictors is useful, consistent with a sparse representation of the prediction problem. Kohns and Szendrei (2021) found the Horseshoe prior to work well for quantile forecasting with many predictors.

- Lasso: The Lasso prior is a special case of the Normal-Gamma prior of Brown and Griffin (2010). The Lasso involves setting u and π to Gamma distributions: $\psi_{\tau j} \sim \mathcal{G}(1, \lambda_\tau/2)$ and $\lambda_\tau \sim \mathcal{G}(c_0, d_0)$. We set the hyperparameters $c_0 = d_0 = 0$, implying heavy global shrinkage. The marginal prior of the coefficients exhibits fat tails. Overall, the Lasso prior offers richer shrinkage patterns than Horseshoe and Ridge.

2.1.2 Gaussian Process Regressions

The Gaussian Process Regression (Williams and Rasmussen, 2006) is a non-parametric method that was recently used for inflation forecasting by Clark, Huber, Koop, and Marcellino (2022). It elicits a process prior on the function $g_\tau(\mathbf{x}_t)$:

$$g_\tau(\mathbf{x}_t) \sim \mathcal{GP}\left(\mu_\tau(\mathbf{x}_t), \mathcal{K}(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}})\right), \tag{4}$$

where we set the mean function $\mu_\tau(\mathbf{x}_t)$ 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, t =1, ..., T.

As $\mathbf{x}_t$ is observed at discrete points in time, $\mathbf{g}_\tau = (g_\tau(\mathbf{x}_1), \ldots, g_\tau(\mathbf{x}_T))'$:

$$\mathbf{g}_\tau \sim \mathcal{N}\left(\mathbf{0}_T, \mathbf{K}(\mathbf{w})\right), \tag{5}$$

where $\mathbf{K}(\mathbf{w})$ refers to a $T \times T$-dimensional matrix with (t, t)-th element $\mathcal{K}(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}})$.

The type of kernel determines the estimated function. We choose a squared exponential kernel:

$$\mathcal{K}(\mathbf{x}_t, \mathbf{x}_{\mathrm{t}}) = w_1 \times e^{-\frac{w_2}{2}\|\mathbf{x}_t - \mathbf{x}_{\mathrm{t}}\|^2}, \tag{6}$$

where we follow Chaudhuri, Kakde, Sadek, Gonzalez, and Kong (2017) for setting the hyperparameters $\mathbf{w} = (w_1, w_2)^{'}$, which govern the smoothness of the function.

Above we have outlined the function-space view of the GP regression. In the alternative weight-space view, which is convenient for estimation, the GP regression can be expressed as

$$\mathbf{y} = \mathbf{Z}\gamma_\tau + \varepsilon, \tag{7}$$

where $\mathbf{y}$ denotes the stacked dependent variables, $\mathbf{Z}$ represents the lower Cholesky factor of $\mathbf{K}$, and $\gamma_\tau \sim \mathcal{N}(\mathbf{0}_T, \mathbf{I}_T)$.

2.1.3 Quantile Regression Forests

Our last forecasting method is a frequentist non-parametric method, namely QR Forests, an extension of Random Forests (Breiman, 2001) for conditional point estimation to conditional quantile estimation based on an ensemble of trees (Meinshausen, 2006). Random Forests and QR Forests capture non-linear predictive relationships and, especially due to this feature, have been found to perform well in macroeconomic forecasting (see, e.g., Medeiros, Vasconcelos, Veiga, and Zilberman, 2021; Clark, Huber, Koop, Marcellino, and Pfarrhofer, 2022).

Random Forests grow a large number of trees by using n independent observations

$$(Y_i, X_i), i = 1, \ldots, n,$$

where Y is the variable of interest and X is a (possibly high-dimensional) predictor variable. For ease of notation we drop time subscripts. For each tree and in each node, Random Forests use a random subset of predictors to split on.[3] The intuition of this random selection is to de-correlate the trees and thus to decrease the variance of the forecasts. In Random Forests, the conditional mean prediction of Y, given $X = x$, is generated as the weighted sum over all observations:

$$\widehat{\mu}(x) = \sum_{i=1}^{n} w_i(x) Y_i, \tag{8}$$

where the weights $w_i(x)$ are computed over the collection of trees. In each tree, the conditional mean prediction is the simple average of all observations that fall into the same leaf when dropping down x; the remaining observations are neglected.

Meinshausen (2006) extended the Random Forests to QR Forests. The conditional distribution function y, given $X = x$, is

$$F(y|X = x) = P(Y \leq y|X = x) = \mathbb{E}\left(\mathbb{1}_{\{Y \leq y\}}|X = x\right). \tag{9}$$

[3]In our empirical work, for a p-dimensional predictive variable, at each node we use the default choice of $\sqrt{p}$ randomly selected predictors.

Instead of approximating the conditional mean $\mathbb{E}\left(Y|X=x\right)$ in case of Random Forests, for QR Forests, $\mathbb{E}\left(\mathbb{1}_{\{Y\leq y\}}|X=x\right)$ is approximated by the weighted mean over the observations $\mathbb{1}_{\{Y\leq y\}}$,

$$\widehat{F}\left(y|X=x\right)=\sum_{i=1}^{n}w_i\left(x\right)\mathbb{1}_{\{Y\leq y\}}, \tag{10}$$

where $w_i\left(x\right)$ are the same weights as for Random Forests. Based on $\widehat{F}\left(y|X=x\right)$, we can estimate the desired conditional α-quantile $Q_\alpha\left(x\right)$ as

$$\widehat{Q}_\alpha\left(x\right)=\inf\left(y:\widehat{F}\left(y|X=x\right)\geq\alpha\right). \tag{11}$$

An important difference between QR Forests and Random Forests is that, for each node in each tree, Random Forests keep just the mean of the observations that fall into the respective node, while QR Forests store the values of all observations in the respective node for computing the conditional distribution.

2.2 Probabilistic topic models

We use topic models to extract information from newspaper articles and to create textual predictors. These models are predominantly data-driven and use a probabilistic approach to identify themes within a large set of written documents. In contrast to dictionary-based and/or Boolean approaches, topic models are initially context-agnostic, finding word clusters (topics) solely based on the co-occurrence of words.[4]

The most prominent topic model is latent Dirichlet allocation (LDA) by Blei, Ng, and Jordan (2003). It posits that documents are generated by a stochastic process where each text is a mixture of latent topics and each topic is a probability distribution over the same vocabulary, but with different probabilities for each word. Despite its prominence and advantages, LDA cannot account for the fact that certain topics tend to co-occur together within documents (e.g., inflation and commodity prices). We therefore use the

[4]Studies using promising (supervised) dictionary-based methods include Kalamara, Turrell, Redl, Kapetanios, and Kapadia (2022), Shapiro, Sudhof, and Wilson (2022) and Barbaglia, Consoli, and Manzan (2022).

more sophisticated correlated topic model (CTM) by Blei and Lafferty (2007) which has been developed to address this limitation.

Figure 1 shows a graphical model of the generative process assumed by the CTM where edges denote dependency, nodes are random variables, and plates are replicated variables. The only observable variables of the model are the words (w).

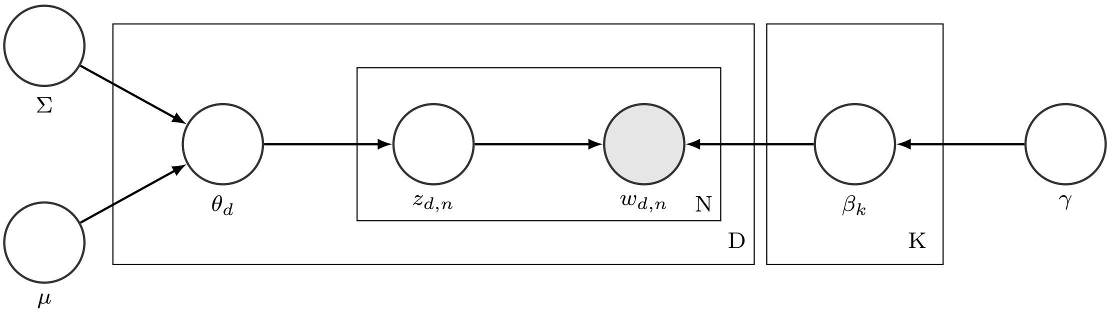

Figure 1: Generative process of the CTM based on Blei and Lafferty (2007).

The key difference between LDA and the CTM is the assumption for the topic proportions, θ_d. The CTM assumes that topic proportions arise from a logistic normal distribution—which has a mean vector (μ) and a covariance matrix (Σ)—in contrast to LDA, which assumes that topic proportions arise from a Dirichlet distribution. Consistent with the more realistic assumptions of correlating topics, the CTM yields higher values for statistics that measure the predictive performance regarding unseen documents (Blei and Lafferty, 2007). The generative process of the CTM can be written as follows (local mathematical notation):

1. K topics of length V (unique vocabulary) are drawn from the Dirichlet distribution with input vector γ:
$$\beta_k \sim Dir(\gamma).$$

2. For each document d, topic proportions (θ_d) of length K are drawn from the logistic

normal distribution:

$$\eta_d \sim \mathcal{N}(\mu, \Sigma)$$
$$\theta_{d,k} = \frac{\exp(\eta_{d,k})}{\sum_{i=1}^{k} \exp(\eta_{d,i})}.$$

(a) For each word n, a topic assignment is drawn from the multinomial distribution:

$$z_{d,n} | \theta_d \sim Mult(\theta_d).$$

(b) Each word is drawn from the multinomial distribution:

$$w_{d,n} | z_{d,n}, \beta_{1:K} \sim Mult(\beta_{z_{d,n}}).$$

We use the *partially collapsed variational EM algorithm* by Roberts, Stewart, and Airoldi (2016) to estimate the CTM. The approach is implemented in the `R`-package `stm` by Roberts, Stewart, and Tingley (2019). We are particularly interested in estimating θ_d, namely the topic proportions of each document, whose aggregates serve as our textual predictors; see Section 3.2.2.

3 Empirical work

3.1 Forecasting setup

We generate monthly quantile now- and one-month-ahead forecasts for employment, inflation, industrial production, and consumer sentiment. Depending on the setting, we incorporate *FRED* predictors, textual predictors, or both together. We detail our predictors in Section 3.2. In addition, all model specifications include 12 lags of the respective (transformed) variable of interest.[5]

For our variables of interest and the *FRED* predictors we use vintage data from the database of McCracken and Ng (2016). Our estimation sample starts in 1980:06, when

[5] The variables are transformed according to Table B in the Appendix.

the news data series start. We run recursive estimations based on an expanding window. Our evaluation periods ranges from 1999:10 to 2021:12.

For nowcasts of a given month, we include macroeconomic predictors from the month before due to the publication lag, while we include textual and financial[6] predictors from the month to be forecasted. For example, if we are at the end of December and produce a nowcast for December, we use the macroeconomic predictors from November released in December, and the financial and textual predictors from December. Similarly, for one-month-ahead forecasts, if we are at the end of December and produce a prediction for January, we use the macroeconomic predictors from November released in December and the financial and textual predictors from December.

We evaluate our forecasting models with the quantile score (QS), which is computed as

$$QS_{\tau,t+h} = (y_{t+h} - Q_{\tau,t+h}) \left(\tau - \mathbb{1}_{\{y_{t+h} \leq Q_{\tau,t+h}\}} \right), \tag{12}$$

where y_{t+h} is the actual outcome of the variable of interest in $t+h$, $Q_{\tau,t+h}$ denotes the forecast of quantile τ for $t+h$. The indicator function $\mathbb{1}_{\{y_{t+h} \leq Q_{\tau,t+h}\}}$ takes on a value of 1 if the outcome is not higher than the quantile forecast, and 0 otherwise.

3.2 Predictor sets

3.2.1 Economic predictors

Our macroeconomic predictors are from the McCracken and Ng (2016) *FRED-MD* database. We pick all predictors from the database that are available at the end of the sample as well as the beginning. The predictors can be classified into eight categories: (i) output and income, (ii) labor market, (iii) housing, (iv) consumption, orders, and inventories, (v) money and credit, (vi) interest and exchange rates, (vii) prices, and (viii) stock market. For the classification of the variables, see `https://www.ssc.wisc.edu/~bhansen/econometrics/FRED-MD_description.pdf`.

[6]See Table B in the Appendix for which variables are classified as financial predictors.

3.2.2 Textual predictors

We used the legal database LexisNexis to download 793,013 economically related newspaper articles from *The New York Times* and *The Washington Post* between 1980:06 and 2021:12. We then conducted Part-of-Speech-Tagging (Benoit and Matsuo, 2022) to remove anything but nouns from the articles. Our reason for this choice is that topic models aim to summarize the *content* of documents, which is predominantly described by nouns, in contrast to sentiment analysis which aims to describe the documents' *tone*. In addition, Martin and Johnson (2015) found highest values of *semantic coherence* when using a nouns-only approach, a metric that strongly correlates with human judgement.

We tokenized the documents into single words, removed punctuation, numbers, symbols, stopwords, etc., and constructed a document-term matrix (dtm). A dtm counts how often a certain word (column) occurs within a certain document (row). We then computed term-frequency inverse-document-frequency values for each word to extract the 10,000 most relevant terms until 1999:09. The final dtm served as the input for the CTM. In addition, the number of topics K has to be given as an input by the researcher. Following Larsen and Thorsrud (2019), Thorsrud (2020) and Ellingsen, Larsen, and Thorsrud (2022), we set the number of topics to 80.

We estimated for each document on each day 80 topic proportions ($\hat{\theta}_d$) based on the newspaper articles until 1999:09. After then, we computed the topic proportions OOS to exclude any look-ahead bias, similar to Ellingsen, Larsen, and Thorsrud (2022). Finally, for a given month, we computed the simple average over all documents' estimated topic proportions. We use the averages of topic proportions as news attention measures in our empirical analyses. Figure 2 shows the trajectories of four selected topics.[7]. The figures show that our topics capture important political and economic events such as several debt crises in Mexico, Asia and Europe (Topic 9), the beginning of the Gulf War in 1991 (Topic 27) and the Great Recession which emanated in the housing market (Topic 46).

[7]The top five terms of all topics are shown in the Appendix in Table A.

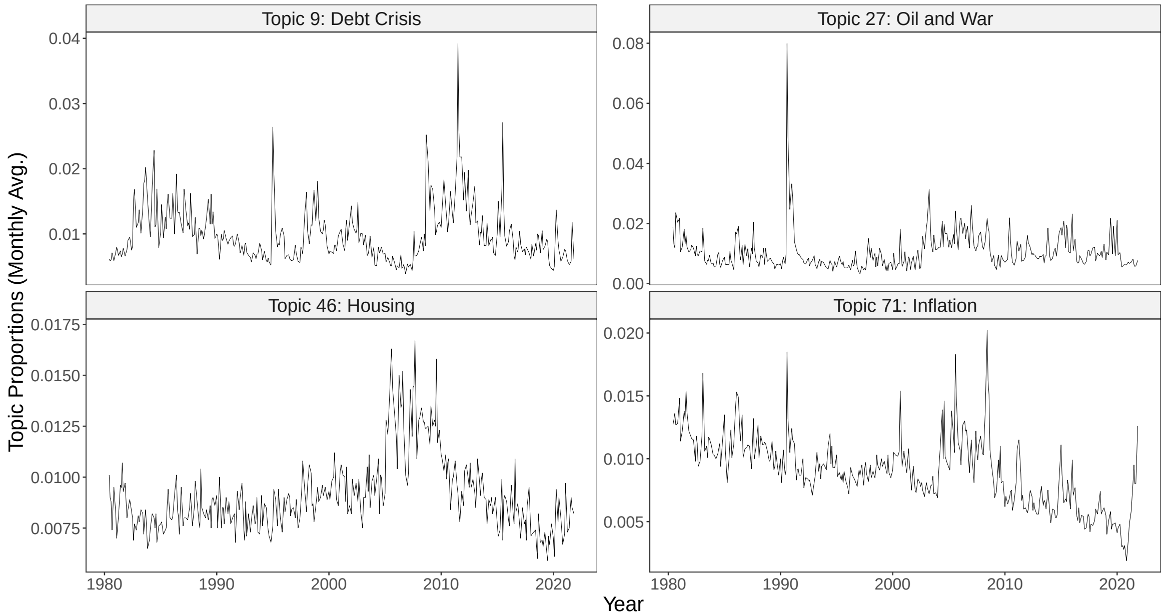

Figure 2: Four selected topic proportions (monthly averages) based on the CTM.

Our forecast results remain robust for different choices. For instance, following Adämmer and Schüssler (2020), who use the CTM and a similar corpus, we computed 100 instead of 80 topics. In addition, the CTM is nested within the more sophisticated structural topic model (STM) by Roberts, Stewart, and Airoldi (2016), which further allows to include covariates. We estimated an STM to account for our two different news sources. Finally, we estimated all models with 15,000 unique words.[8]

3.3 Forecast results

Figure 3 and 4 summarize the results for the now- and the one-month-ahead forecasts, respectively. Forecast accuracy is assessed by quantile scores across different quantiles τ: $\tau = 5\%, 10\%, 25\%, 50\%, 75\%, 90\%, 95\%$. A quantile AR(1) model serves as our benchmark. Quantile scores below (above) one indicate more (less) precise forecasts compared to the benchmark model.

We observe the following patterns: first, concerning the news attention measures, the combination of macroeconomic predictors and textual predictors leads to accuracy gains

[8]The results are available upon request.

in many cases compared to the setting with macroeconomic or textual predictors only. In the cases where adding textual predictors does not improve forecast performance, it does not materially harm either. The incremental value from adding textual predictors is pronounced in the tails and more so for the forecasting models that feature a linear predictive relationship. Improved tail forecasting with textual data points to a scenario where textual predictors are especially helpful in extreme economic environments, where timely news data might reflect the economic overall picture and are useful predictors for macroeconomic variables. In times like the Great Recession or the COVID-19 pandemic, developments like uncertainty and political changes might have been more closely captured than by hard economic indicators. In Horseshoe, Lasso and Ridge, textual predictors might compensate the non-modeled complexity in form of a non-linear predictive relationship.

Second, in both figures, the quantile scores of the linear models tend to be U-shaped, whereas the quantile scores of the models that feature a non-linear predictive relationships are mainly hump-shaped. Hence, the linear models generate comparatively precise forecasts in the center of the distribution whereas the non-linear models shine especially in forecasting the tails. In either case, the addition of textual data has a lower impact in the center of the distribution than in the tails.

Third, within the class of methods that feature a non-linear predictive relationship, Gaussian processes have a slight edge over QR forests across variables and quantiles, with more cases where they produce more precise and significantly better forecasts than an AR(1) model according to the Diebold and Mariano (1995) test. Within the class of linear models, the Horseshoe shrinkage prior overall underperforms the Lasso and Ridge shrinkage priors in the tails. Ridge, as a *purely global* shrinkage prior, is at least on par with Lasso which, as a *global-local* shrinkage prior, applies predictor-specific shrinkage. Hence, the richer shrinkage patterns offered by Lasso do not pay off in this analysis. These results are consistent with a dense representation of the prediction problem where many weak predictors are relevant rather than with a sparse structure where few important predictors can be selected and the others are dismissed (Giannone, Lenza, and Primiceri, 2021).

Fourth, we find the following key patterns of predictability for our four target variables. For employment, we observe substantial outperformance in the right tail for now- and forecasts in case of the Gaussian processes; regarding inflation now- and forecasts, accuracy gains are most pronounced in the tails for Gaussian processes and QR forests. Here, Ridge becomes competitive with these methods once textual predictors are added. For industrial production now- and forecasts, overall Gaussian processes exhibit the strongest forecast performance, with QR forests as a close second. Again, the methods with a linear predictive relationship become competitive once textual predictors are added. For consumer sentiment (now- and forecasts), quantile scores markedly improve in the left tail when textual predictors are added, in particular for the methods with a linear predictive relationship. This result is interesting from an information processing aspect, supporting the notion that news data play an important role for households in forming their expectations (Larsen, Thorsrud, and Zhulanova, 2021).

3.4 Which predictors determine the quantile forecasts?

Since we include forecasting methods that feature non-linear predictive relationships, it is not obvious how to pin down the marginal effect of any predictor on the variable of interest. Further, we use heterogeneous forecasting methods, and we wish to ensure comparability for measures of predictor importance across the methods. To accomplish this task and to shed light on the predictors with the highest impact, for each forecasting model, we rely on a linear approximation to the predictive distribution as proposed by Woody, Carvalho, and Murray (2021). Concretely, we aim to approximate the quantile predictions $Q_{\tau,t+h}$ with a linear regression model that uses regularization. For each quantile τ, the following Lasso-type optimization problem is solved:

$$\beta_\tau^* = \arg\min_{\beta_\tau} \sum_{t=t_0}^{T-h} \left(Q_{\tau,t+h} - \beta_\tau' \mathbf{x}_t\right)^2 + \lambda \sum_{j=1}^{K} |\beta_{\tau,j}| \,, \tag{13}$$

where t_0 denotes the beginning of the hold-out period, $\beta_\tau = (\beta_{\tau,1}, \ldots, \beta_{\tau,K})'$ denotes the vector of coefficients, and $\lambda \geq 0$ is a penalty parameter that controls the shrinkage intensity and is chosen via cross-validation. For the predictor importance analysis we use our most comprehensive set of predictor variables, including both *FRED* and textual predictors. We focus on the 10%-quantile because our previous analysis has shown the most interesting patterns in the lower tails. Figure 5 and Figure 6 report the five most influential predictors at the 10%-quantile for now- and forecasts, respectively. Importance is measured by the absolute values of the coefficients associated with the (standardized) predictors. Overall, we observe a fair degree of overlap across the forecasting methods regarding the most influential variables.

For employment, mostly *FRED* predictors related to the labor market are included in the top five. Further, both Ridge and the Gaussian Process Regressions include the "Regulation and Law" news topic among the most important predictors; for inflation, *FRED* predictors related to prices are in the lead. Regarding news predictors, Gaussian processes and QR Forests agree on the "Housing" topic for one-month-ahead forecasts; for production, the most influential *FRED* predictors are spread among variables related to the labor market, money & credit, and housing. For nowcasts of production, Horseshoe and Lasso select the "State of the Economy" topic as an important predictor. For one-month-ahead forecasts of production, in Lasso, Ridge, and Gaussian processes, the "Regulation and Law" topic appears in the top five; for consumer sentiment, *FRED* variables related to interest and exchange rates prevail. For nowcasts, all forecasting methods select the "State of Economy" topic as top five predictor. For one-month-ahead forecasts of consumer sentiment, all forecasting methods except Lasso agree on the "Debt Crisis" topic. Especially for consumer sentiment forecasts, the relatively high number of news predictors in the top five is apparent and consistent with the strong forecast performance of textual predictors for sentiment (see Figure 4). Altogether, the predictors that appear as most influential for the respective target variable make sense from an economic perspective.

Another interesting piece of information is how many *FRED* and textual predictors were chosen in the Lasso-regression (13). Figure 7 and 8 show the number of nonzero coefficients for the now- and one-step-ahead forecasts, respectively. We focus on the 10%, 50% and 90% quantiles here. Overall, the structure for the one-step-ahead forecasts is substantially sparser than in case of the nowcasts. Across different target variables and quantiles, the structure of included *FRED* and textual predictors is balanced. However, we observe a comparatively high portion of selected textual predictors for consumer sentiment, corroborating their important role for this variable.

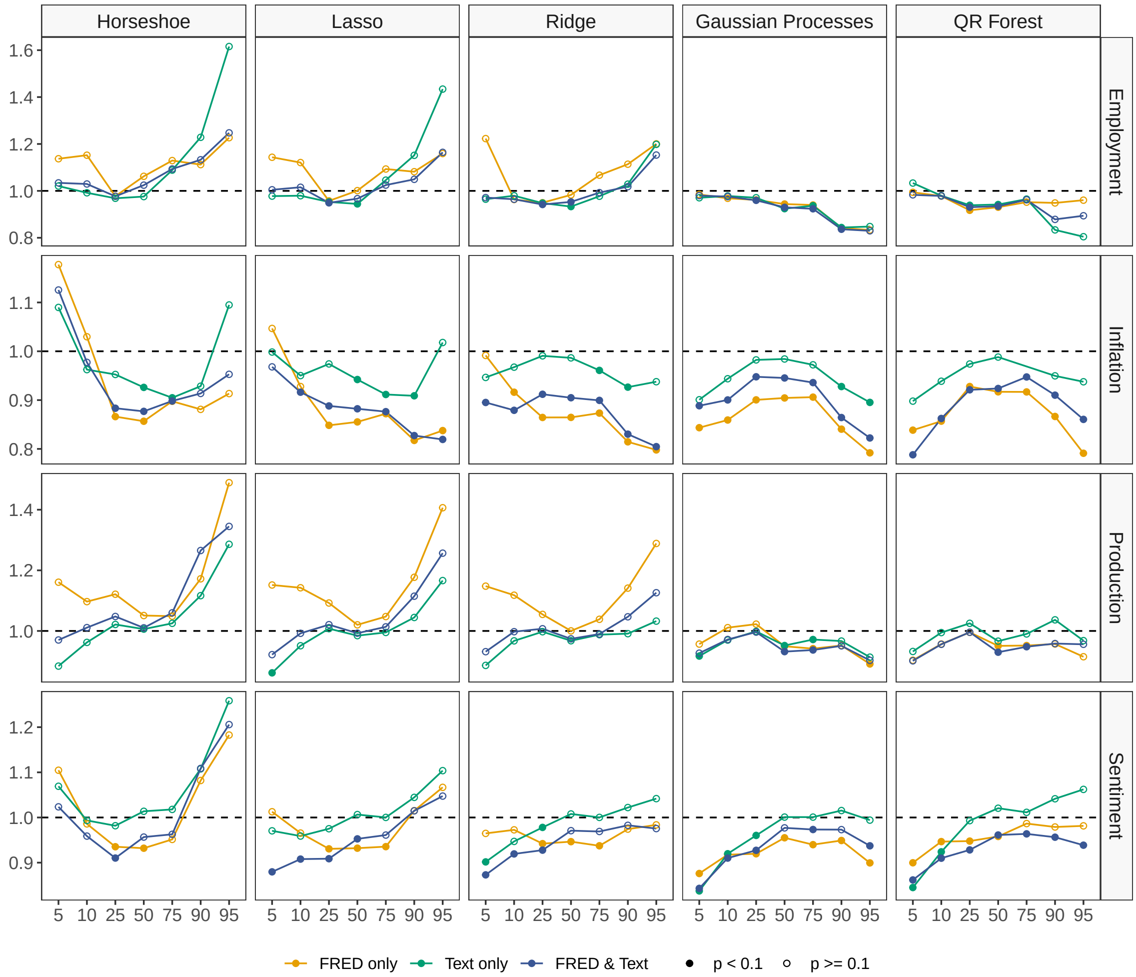

Figure 3: Nowcast (h = 0) quantile scores. The dotted black horizontal line shows the quantile score of the AR(1) benchmark which is standardized to 1.0. Scores below (above) 1.0 indicate more (less) precise forecasts for a given quantile compared to the AR(1) benchmark. Inside colored dots indicate significantly higher forecast accuracy compared to the AR(1) benchmark according to a one-tailed Diebold and Mariano (1995) test at the 10% level.

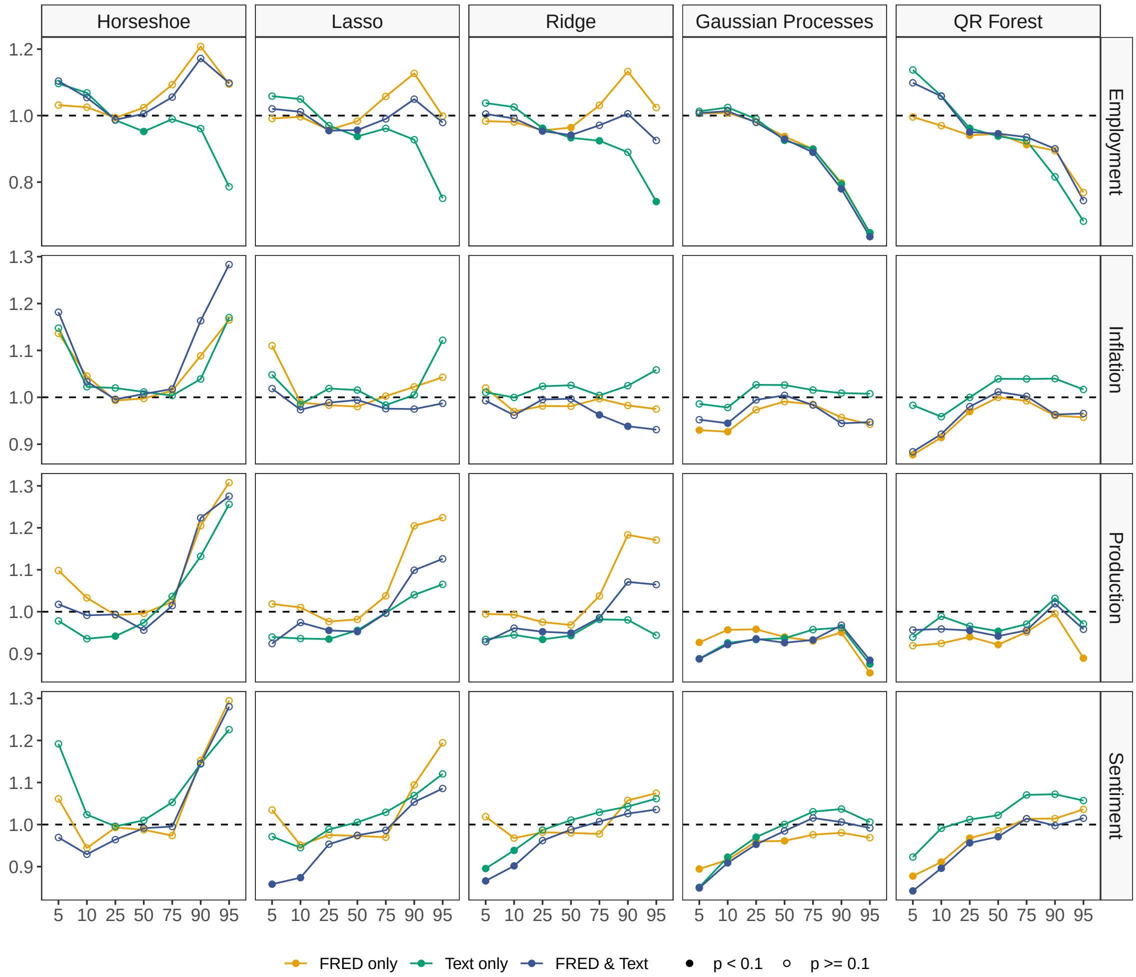

Figure 4: One-step-ahead (h = 1) quantile scores. The dotted black horizontal line shows the quantile score of the AR(1) benchmark which is standardized to 1.0. Scores below (above) 1.0 indicate more (less) precise forecasts for a given quantile compared to the AR(1) benchmark. Inside colored dots indicate significantly higher forecast accuracy compared to the AR(1) benchmark according to a one-tailed Diebold and Mariano (1995) test at the 10% level.

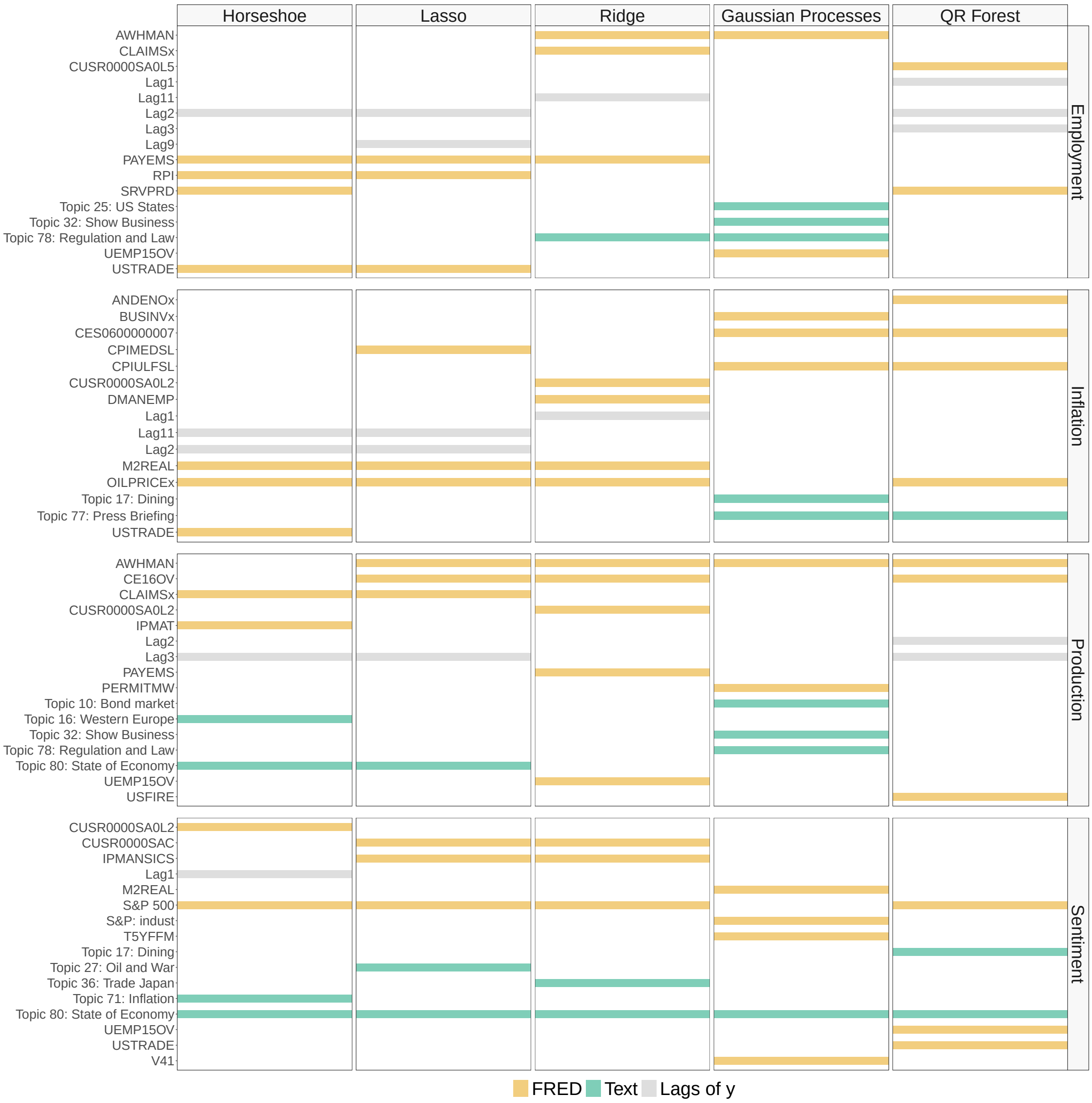

Figure 5: Variable importance for nowcasts at the 10%-quantile ($h = 0$, $\tau = 10\%$).

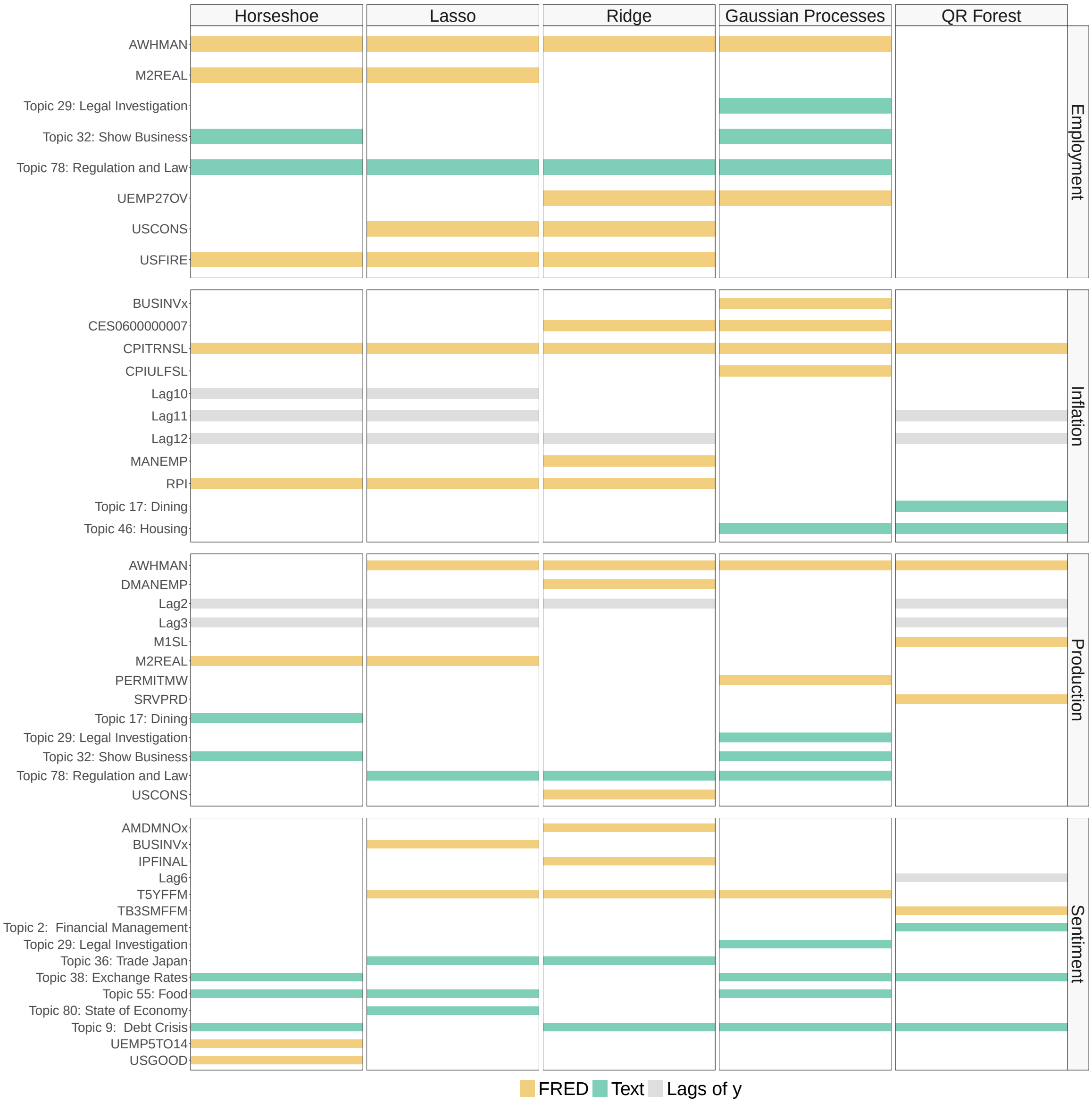

Figure 6: Variable importance for one-step-ahead forecasts at the 10%-quantile ($h = 1, \tau = 10\%$).

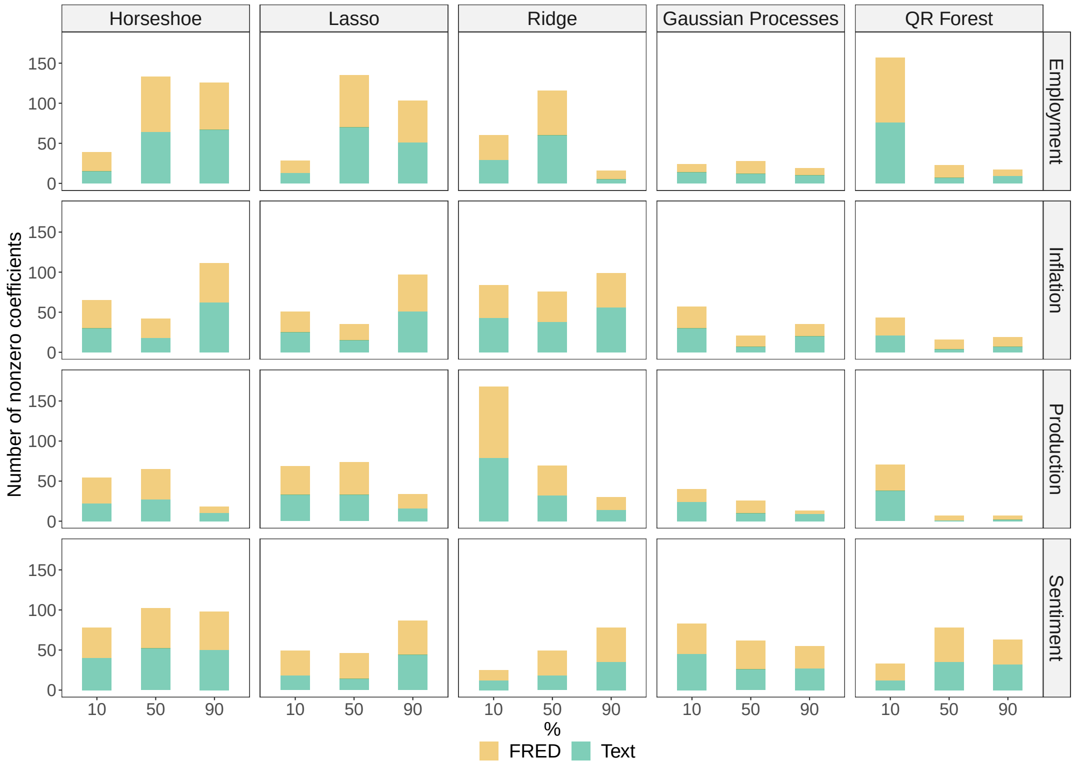

Figure 7: Variable selection for nowcasts ($h = 0$) based on Equation (13).

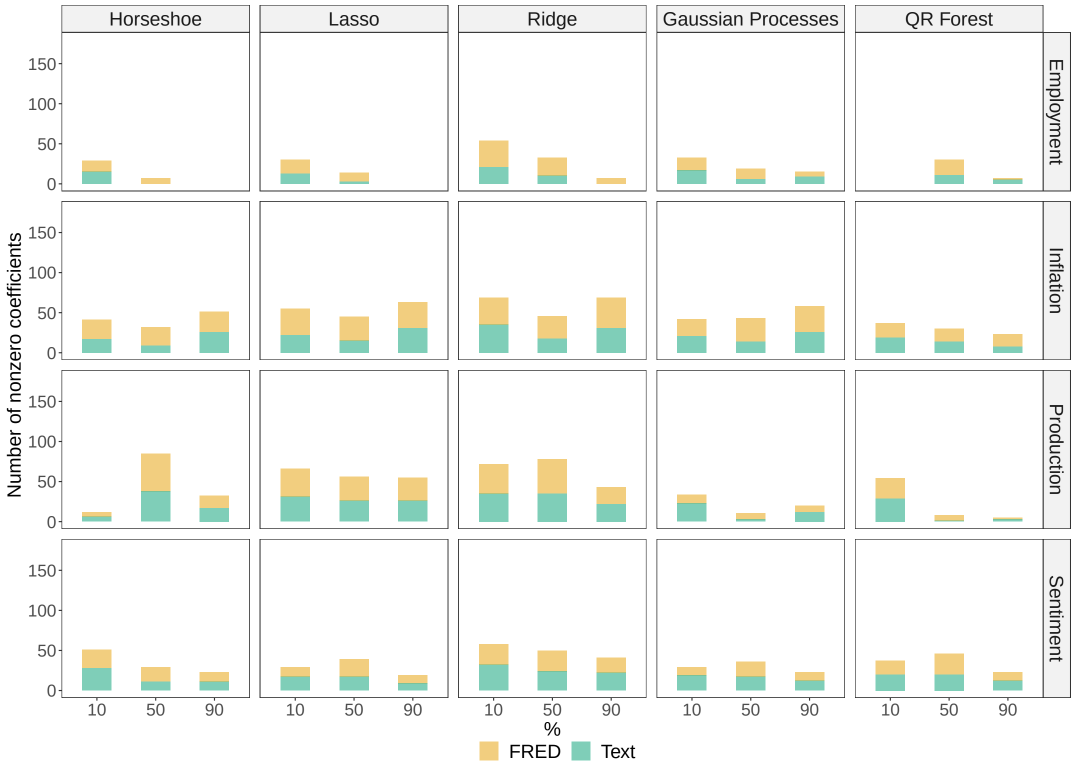

Figure 8: Variable selection for one-step-ahead forecasts ($h = 1$) based on Equation (13).

4 Concluding remarks

We have analyzed the value added by textual predictors for quantile now- and forecasts of macroeconomic time series. Our high-dimensional setup comprised forecasting methods with both linear and non-linear quantile-specific predictive relationships, and we considered different sets of predictors.

Overall, Gaussian Process Regressions and QR Forests prevailed in terms of tail forecast accuracy, suggesting that non-linear predictive relationships are a promising route to follow in tail forecasting. Although forecast performance varied across quantiles and target variables, altogether, combinations of *FRED* and textual predictors produced the most accurate forecasts, especially in the tails. In cases where adding the news attention measures did not provide gains in forecast accuracy, they were not detrimental either. Hence, the benefits from incorporating textual data tend to outweigh the risks.

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A Topics and their keywords

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
bill	target	committee	dollar	sale	worker	date	country	debt	bond
legislation	balance	chairman	currency	unit	union	start	world	mexico	percent
measure	release	issue	exchange	auto	labor	correction	nation	brazil	rate
amendment	goal	vote	yen	maker	wage	schedule	government	crisis	yield
provision	ratio	senator	mark	analyst	strike	delay	economy	payment	note
Topic 11	Topic 12	Topic 13	Topic 14	Topic 15	Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
president	member	subc	israel	percent	germany	restaurant	car	rate	america
office	board	appropriation	peace	increase	france	wine	truck	loan	problem
director	plan	subcommittee	lebanon	figure	britain	bar	vehicle	interest	question
staff	commission	budget	egypt	decline	west	dinner	bus	mortgage	idea
washington	proposal	committee	syria	rate	east	coffee	driver	credit	fact
Topic 21	Topic 22	Topic 23	Topic 24	Topic 25	Topic 26	Topic 27	Topic 28	Topic 29	Topic 30
police	weapon	book	speech	state	south	oil	cent	lawyer	quarter
violence	arm	newspaper	event	california	black	iraq	contract	case	share
death	missile	paper	crowd	jersey	africa	iran	gasoline	charge	percent
attack	korea	magazine	visit	governor	minority	barrel	future	official	profit
security	defense	page	message	texas	white	gas	delivery	investigation	loss
Topic 31	Topic 32	Topic 33	Topic 34	Topic 35	Topic 36	Topic 37	Topic 38	Topic 39	Topic 40
government	show	tax	stock	child	trade	benefit	gold	group	hotel
poland	los	budget	share	family	japan	employee	dollar	organization	room
protest	angeles	cut	point	life	export	cost	york	community	tourist
demonstration	san	taxis	index	parent	import	worker	rate	church	visitor
leader	film	spending	investor	mother	product	pay	trading	movement	beach
Topic 41	Topic 42	Topic 43	Topic 44	Topic 45	Topic 46	Topic 47	Topic 48	Topic 49	Topic 50
building	computer	campaign	drug	official	home	job	city	bank	report
housing	technology	candidate	crime	policy	house	work	york	loan	study
project	system	voter	police	administration	property	force	resident	banking	number
construction	machine	election	prison	issue	estate	unemployment	neighborhood	institution	research
apartment	information	poll	officer	effort	owner	employment	mayor	saving	survey
Topic 51	Topic 52	Topic 53	Topic 54	Topic 55	Topic 56	Topic 57	Topic 58	Topic 59	Topic 60
agreement	plane	china	united	food	party	program	health	rate	market
talk	space	beijing	states	meat	election	government	care	economy	future
negotiation	ship	taiwan	washington	fruit	leader	agency	insurance	growth	firm
deal	aircraft	hong	cuba	animal	government	welfare	hospital	inflation	investor
side	air	kong	country	product	power	money	doctor	economist	broker
Topic 61	Topic 62	Topic 63	Topic 64	Topic 65	Topic 66	Topic 67	Topic 68	Topic 69	Topic 70
school	company	service	woman	aid	store	plant	fund	county	business
student	firm	airline	man	guerrilla	chain	steel	money	area	industry
education	executive	card	life	nicaragua	retailer	power	investment	maryland	economy
college	deal	fare	friend	rebel	customer	energy	investor	official	corporation
teacher	management	phone	guy	government	shopping	utility	return	washington	executive
Topic 71	Topic 72	Topic 73	Topic 74	Topic 75	Topic 76	Topic 77	Topic 78	Topic 79	Topic 80
price	union	vietnam	farm	building	water	meeting	law	war	nation
consumer	soviet	refugee	farmer	room	land	conference	court	force	effort
cost	russia	immigrant	crop	wall	mile	news	case	troop	part
increase	moscow	kong	grain	floor	town	leader	rule	army	million
producer	republic	hong	land	street	area	statement	regulation	military	end

B Variable transformations

ID	FRED Code	Description	Transformation Codes	Financial
1	RPI	Real Personal Income	5	
2	W875RX1	Real personal income ex transfer receipts	5	
4	CMRMTSPLx	Real Manu. and Trade Industries Sales	5	
5	RETAILx	Retail and Food Services Sales	5	
6	INDPRO	IP Index	5	
7	IPFPNSS	IP: Final Products and Nonindustrial Supplies	5	
8	IPFINAL	IP: Final Products (Market Group)	5	
9	IPCONGD	IP: Consumer Goods	5	
13	IPMAT	IP: Materials	5	
16	IPMANSICS	IP: Manufacturing (SIC)	5	
20	CUMFNS	Capacity Utilization: Manufacturing	2	
23	CLF16OV	Civilian Labor Force	5	
24	CE16OV	Civilian Employment	5	
25	UNRATE	Civilian Unemployment Rate	2	
26	UEMPMEAN	Average Duration of Unemployment (Weeks)	2	
27	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	5	
28	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	5	
29	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	5	
30	UEMP15T26	Civilians Unemployed for 15-26 Weeks	5	
31	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	5	
32	CLAIMSx	Initial Claims	5	
33	PAYEMS	All Employees: Total nonfarm	5	
34	USGOOD	All Employees: Goods-Producing Industries	5	
35	CES1021000001	All Employees: Mining and Logging: Mining	5	
36	USCONS	All Employees: Construction	5	
37	MANEMP	All Employees: Manufacturing	5	
38	DMANEMP	All Employees: Durable goods	5	
39	NDMANEMP	All Employees: Nondurable goods	5	
40	SRVPRD	All Employees: Service-Providing Industries	5	
42	USWTRADE	All Employees: Wholesale Trade	5	
43	USTRADE	All Employees: Retail Trade	5	
44	USFIRE	All Employees: Financial Activities	5	
45	USGOVT	All Employees: Government	5	
46	CES0600000007	Avg Weekly Hours : Goods-Producing	1	
47	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	2	
48	AWHMAN	Avg Weekly Hours : Manufacturing	1	
50	HOUST	Housing Starts: Total New Privately Owned	4	
51	HOUSTNE	Housing Starts, Northeast	4	
52	HOUSTMW	Housing Starts, Midwest	4	
53	HOUSTS	Housing Starts, South	4	
54	HOUSTW	Housing Starts, West	4	
55	PERMIT	New Private Housing Permits (SAAR)	4	
56	PERMITNE	New Private Housing Permits, Northeast (SAAR)	4	
57	PERMITMW	New Private Housing Permits, Midwest (SAAR)	4	
58	PERMITS	New Private Housing Permits, South (SAAR)	4	
59	PERMITW	New Private Housing Permits, West (SAAR)	4	
65	AMDMNOx	New Orders for Durable Goods	5	
66	ANDENOx	New Orders for Nondefense Capital Goods	5	
67	AMDMUOx	Un lled Orders for Durable Goods	5	
68	BUSINVx	Total Business Inventories	5	
69	ISRATIOx	Total Business: Inventories to Sales Ratio	2	
70	M1SL	M1 Money Stock	6	

ID	FRED Code	Description	Transformation Codes	Financial
71	M2SL	M2 Money Stock	6	
72	M2REAL	Real M2 Money Stock	5	
74	TOTRESNS	Total Reserves of Depository Institutions	6	
75	NONBORRES	Reserves Of Depository Institutions	7	
76	BUSLOANS	Commercial and Industrial Loans	6	
77	REALLN	Real Estate Loans at All Commercial Banks	6	
78	NONREVSL	Total Nonrevolving Credit	6	
79	CONSPI	Nonrevolving consumer credit to Personal Income	2	
80	S&P 500	S&P s Common Stock Price Index: Composite	5	X
81	S&P: indust	S&P s Common Stock Price Index: Industrials	5	X
82	S&P div yield	S&P s Composite Common Stock: Dividend Yield	2	
83	S&P PE ratio	S&P s Composite Common Stock: Price-Earnings Ratio	5	
84	FEDFUNDS	Effective Federal Funds Rate	2	X
86	TB3MS	3-Month Treasury Bill:	2	X
87	TB6MS	6-Month Treasury Bill:	2	X
88	GS1	1-Year Treasury Rate	2	X
89	GS5	5-Year Treasury Rate	2	X
90	GS10	10-Year Treasury Rate	2	X
91	AAA	Moody s Seasoned Aaa Corporate Bond Yield	2	X
92	BAA	Moody s Seasoned Baa Corporate Bond Yield	2	X
94	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	1	X
95	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	1	X
96	T1YFFM	1-Year Treasury C Minus FEDFUNDS	1	X
97	T5YFFM	5-Year Treasury C Minus FEDFUNDS	1	X
98	T10YFFM	10-Year Treasury C Minus FEDFUNDS	1	X
99	AAAFFM	Moody s Aaa Corporate Bond Minus FEDFUNDS	1	X
100	BAAFFM	Moody s Baa Corporate Bond Minus FEDFUNDS	1	X
102	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	5	X
103	EXJPUSx	Japan / U.S. Foreign Exchange Rate	5	X
104	EXUSUKx	U.S. / U.K. Foreign Exchange Rate	5	X
105	EXCAUSx	Canada / U.S. Foreign Exchange Rate	5	X
110	OILPRICEx	Crude Oil, spliced WTI and Cushing	6	
111	PPICMM	PPI: Metals and metal products:	6	
113	CPIAUCSL	CPI : All Items	6	
114	CPIAPPSL	CPI : Apparel	6	
115	CPITRNSL	CPI : Transportation	6	
116	CPIMEDSL	CPI : Medical Care	6	
117	CUSR0000SAC	CPI : Commodities	6	
118	CUSR0000SAD	CPI : Durables	6	
119	CUSR0000SAS	CPI : Services	6	
120	CPIULFSL	CPI : All Items Less Food	6	
121	CUSR0000SA0L2	CPI : All items less shelter	6	
122	CUSR0000SA0L5	CPI : All items less medical care	6	
123	PCEPI	Personal Cons. Expend.: Chain Index	6	
127	CES0600000008	Avg Hourly Earnings : Goods-Producing	6	
128	CES2000000008	Avg Hourly Earnings : Construction	6	
129	CES3000000008	Avg Hourly Earnings : Manufacturing	6	
130	UMCSENTx	Consumer Sentiment Index	2	

Notes: This table provides an overview of the McCracken and Ng (2016) *FRED-MD* data set. The transformation codes are applied to each time series Y_j and described in : (1) no transformation; (2) Δy_{jt}; (3) $\Delta^2 y_{jt}$; (4) $\log(y_{jt})$; (5) $\Delta \log(y_{jt})$; (6) $\Delta^2 \log(y_{jt})$; (7) $\Delta(y_{jt}/y_{jt-1} - 1)$. Financial variables are indicated by X.