Discussion of Adämmer, Prüser and Schüssler, 2023, "Forecasting macroeconomic tail risk in real time: Do textual data add value?"

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*Views expressed are those of the author and do not necessarily reflect the position of De Nederlandsche Bank.

Main idea paper

- Explore benefits of textual predictors for monthly tail risk forecasts of employment, industrial production, inflation and consumer sentiment in real-time;
- Textual predictors: correlated topic model estimated on English news articles;
- Analyze impact of textual predictors in linear and non-linear models;
- Linear models: linear Bayesian quantile regressions with three shrinkage priors (Ridge, Horseshoe & Lasso) | Non-linear models: Bayesian Gaussian process regressions and Quantile regression forests.

Main insight

- Non-linear models have higher now- and forecasting accuracy in tails of distribution than linear models;
- News topics can increase forecasting accuracy, especially in the left tail of the distribution.

Four main comments

• 1. Timing **real-time** analysis, 2. Use of **survey** indicators, 3. high **volatility** and forecasting accuracy, 4. **dynamic** topic models.



Comment 1: Robustness to shift in timing real-time exercise

- Current version of paper compares real-time forecasting accuracy on last business day of the month, based on FRED-MD database;
- 100 monthly indicators from FRED-MD in paper | 21 financial indicators, 80 news topic proportions;
- News topics & financial indicators known at end-of month, macro-economic indicators have one month **publication delay**;
- Therefore, outcome forecasting horse-race only valid for end-of-month comparison of forecasting accuracy;
- What happens to relative forecasting accuracy of the textual predictors if you shift by a week, two weeks, three weeks (see e.g Bańbura et al., 2013 and Knotek and Zaman, 2022)?
 - Knotek and Zaman (2022) nowcasts for monthly inflation rate on 1st, 8th, 15th, last day and 15th of following month.
 - Main takeaway: smaller publication lags increase forecasting accuracy.



Comment 1: Robustness to shift in timing real-time exercise (cont.)

 Though experiment: shift data availability from end-of-April 2023 to mid-May 2023 using publication calendar of the series included in FRED-MD;

Example: shift two weeks in time, % of variables with same delay as news topics

	April 2023	Mid-May 2023
Financial indicators (%)	21	21
Macro-economic indicators (%)	0	54
Same delay as news-topics (%)	21	75

• Larger nr. of indicators with identical publication delay will (probably) **decrease** value-added textual predictors.

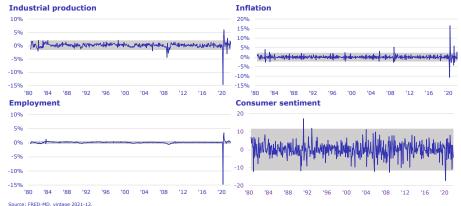


Comment 2: Include more survey indicators

- Only one survey indicator included in real-time database ("Michigan Consumer Sentiment, headline")
- Survey indicators are a "fierce" competitor to news-based data (e.g. Bańbura et al., 2013) because of short(er) publication delays;
- Long list of possible survey indicators in the US; e.g manufacturing PMI (flash: -6 days), ISM services (flash: -6 days), Philadelphia Fed non-manufacturing business outlook survey (-7 days);
- Value added news-indicators decreases when survey information is added (e.g Ellingsen, Larsen and Thorsrud, 2022 and van Dijk en de Winter, 2023)
- Larger nr. of indicators with identical publication delay will (probably) decrease valueadded news-topics



Comment 3: High volatility and forecasting accuracy



Source: FRED-MD, vintage 2021-12. Shaded areas: mean + 3*(standard deviation) over periode 1980-06 until 2008-08.

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Comment 3: High volatility and forecasting accuracy

- When do indicator based models outperform quantile AR?
 - Relatively good forecasting performance of indicator-models vs. simple benchmark models in large part driven by crisis-periods (e.g. Jansen et al, 2018). Hard to beat simple benchmark in tranquil period;
 - Current version paper: Quantile score (QS) are averaged over complete sample; unclear what moves QS over times;
 - Suggestion: Analyze cumulative QS over time (see e.g. Welch and Goyal, 2008 and Borup and Schütte, 2020) or exclude crisis-period from QS;



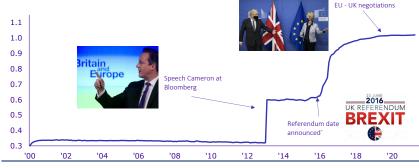
Comment 4: Dynamic word-topic distributions

- Fixed word-topic distribution estimated over the period 1980M6 1999M9 and is not updated over the evaluation period;
- Does not take into account large change in topic content & word use since 1999:
 e.g. Brexit, ECB, euro;
- Probability of new words and words gaining popularity after 1999 are **under**represented in word-topic distributions;
- Topic-document proportions will be strongly influenced, might decrease forecasting accuracy news-topics;
- Suggestion: **Dynamic** topic model (Blei et al, 2006) or **time-varying** topic model (van Dijk and de Winter, 2023);



Comment 4: Dynamic word-topic distributions (cont.)

Example: time variation in "Brexit", within topic "Economics" (van Dijk and de Winter, 2023)

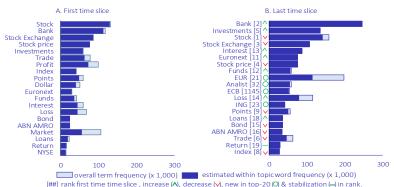


Higher score is more relevant, lambda = 0.6



Comment 4: Dynamic word-topic distributions (cont.)

Example: time variation within topic "Financial Markets" (van Dijk and de Winter, 2023)



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Wrap-up

• Very nice paper combining state-of-the art Bayesian techniques and topic modelling techniques that stimulated further thinking on tail-risk now- and forecasting;

Thank you!



Other comments

- Alternative for Bayesian shrinkage: Extract factors from FRED-MD in tail risk framework (Plagborg-Møller et al., 2020);
- Real-time analysis: which vintages are used for the dependent variable exactly: first release, final release? Might matter (a lot), see e.g. Croushore (2011)
- Robustness test for to number of lags in models (currently 12), structural breaks
 in volatility (e.g. in inflation) and compare forecasting accuracy of correlated topic
 model to plain-vanilla LDA, test for the "optimal" number of topics in topic model;
- Diebold Mariano to determine if linear model(s) are statistically more accurate than non-linear models | Currently: all tests against quantile AR(1);
- Check publication lags in database, for some variables two months or more (e.g. business inventories, real personal income, non-revolving credit), and check for changes in publication lags over time;



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