Forecasting with Economic News

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¹The views expressed are purely those of the writer and may not in any circumstance be regarded as stating an official position of the European Commission.



Sentiment Analysis

Consider news as additional data source for economic forecasting:

- Build fine-grained aspect-based economic sentiment indicators
- Forecast/nowcast in real-time major economic variables in the US
- In-sample and out-of-sample performance assessment
- Explore the performance at different quantile levels

Fine-Grained Aspect-Based Sentiment analysis

	Frequency	Sentiment
Term selection	Baker et al. (2016)	Shapiro et al. (2020)
Topic modeling	Bybee et al. (2019)	Thorsrud (2016)

Our sentiment analysis approach is

Aspect-based: sentiment computed only about a token-of-interest (ToI)

ightarrow identify words that characterizes the ToI based on some **semantic rules**

Fine-grained : assign a sentiment score between [-1,1] to a sentence based on dictionary customized for economic applications

ightarrow **human-annotated scores** of the Loughran & McDonald (2011) lexico

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Natural Language Processing (NLP) pipeline

If the sentence contains the token of interest, apply this NLP pipeline:

- Tokenization and stop word filtering
 - text is split into words
 - removed common words or punctuation (e.g., the, a, :, !, ;-)
- ullet Lemmatization: transform a word in its base form (e.g., is o be)
- Part-Of-Speech and Dependency tagging via SPACY
- Negation handling
- Tense (present, past, future, NA) and location detection
- Assign a sentiment to the words using a set of semantic rules and a customised economic dictionary





News data

Data from Dow Jones Data News Analytics (DNA):

- Articles from January 1984 to end of December 2019
- DNA categories: Commodity/Financial Market, Economic and Corporate/Industrial, Political/General
- 6.6 million articles and 4.2 billion words
- Major US outlets:
 - New York Times
 - Wall Street Journal
 - Washington Post
 - Dallas Morning News
 - San Francisco Chronicle
 - ▶ The Chicago Sun-Times
- 24 economic sentiment indicators (6 topics and 4 tenses)

Tokens-of-Interest (Tol)

We construct six indicators of economic sentiment that capture different aspect of economic activity and policy:

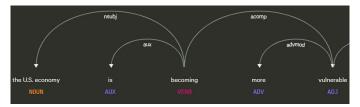
- Economy: economy
- Financial Sector: bank, derivatives, lending, borrowing and permutations of [banking, financial] with [sector, commercial, and investment]
- Inflation: inflation
- Output: manufacturing and permutations of [industrial, manufacturing, construction, factory, auto] with [sector, production, output, activity]
- *Monetary Policy*: central bank, federal reserve, money supply, monetary policy, federal funds, base rate, and interest rate
- Unemployment: unemployment



Example from Wall Street Journal, February 11th, 2016

"Her comments played into the concern that after years of uneven growth, the US economy is becoming more vulnerable to the global slowdown"

- Tol & location : economy & US
- Rule : verb followed by adjectival complement and adverbial modifier
- Verb: become (sentiment: 0; present tense)
- Adjectival complement: vulnerable (sentiment: -0.5)
- Adverbial modifier: more (sentiment: 0.4)
- overall sentiment : -0.5 + (-0.5*0.4) = -0.7



Economic Sentiment Measures



Densities



Forecasting setup

The goal is to predict the first release in day d in period t

- In-sample and out-of-sample with expanding window 2002-19
- Consider forecast horizons h from 1 week to 1 year
- Include all available information at time d h

Real-time variables²:

- Dependent variables: GDPC1, INDPRO, PAYEMS and CPIAUCSL
- additional regressors: Chicago Fed National Activity Index (CFNAI) and National Financial Condition Index (NFCI)
- 24 economic sentiment indicators added one at the time

Forecasting models augmented with sentiment

Unrestricted MIDAS approach (Marcellino Schumacher, 2010)

$$Y_t^d = \sum_{p=1}^P \beta_{h,p} Y_{t-p}^{d-h} + \sum_{q=1}^Q \gamma_{h,q} \mathit{CFNAI}_{t-q}^{d-h} + \sum_{w=1}^W \delta_{h,w} \mathit{NFCI}_{t,w}^{d-h} + \eta_h \mathcal{S}_{d-h} + \epsilon_t^d$$

The forecasting models:

- AR : $\gamma_{h,q}, \delta_{h,w}, \eta_h = 0$ for all w, q
- ARS: the AR model augmented with sentiment $(\gamma_{h,q}, \delta_{h,w} = 0)$
- ullet ARX: the model that includes lags, CFNAI and NFCI $(\eta_h=0)$
- ARXS: ARX model with sentiment

Forecasting models augmented with sentiment

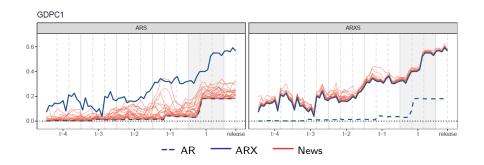
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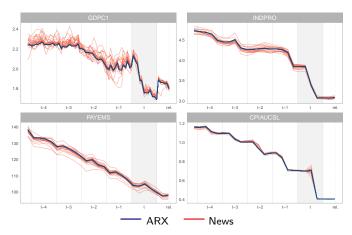
In-sample R^2



- Upward slope R^2 curves: effect of the information flow
- Augmenting AR always useful, in particular at forecasting horizons
- Sentiment useful also in ARX with CFNAI and NFCI

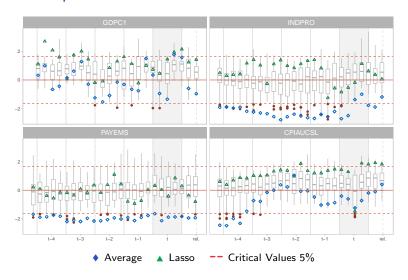
Variable selection

Out-of-sample: RMSPE



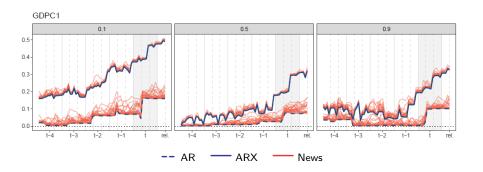
- Macroeconomic releases decrease RMSPE (largest decline in t)
- ullet GDPC1: Economy (fu), Financial Sector (pr/pa) ightarrow max gain 11.4%
- INDPRO: Unemployment (pr), Output (pa) \rightarrow average gain 1.3%

Out-of-sample: DM test statistics



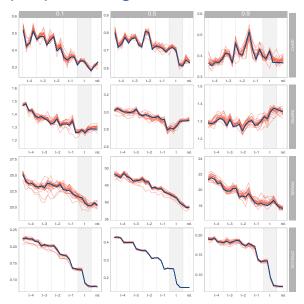
Negative statistics below the critical value: model outperforms the ARX

In-sample: Pseudo- R^2 quantile regression

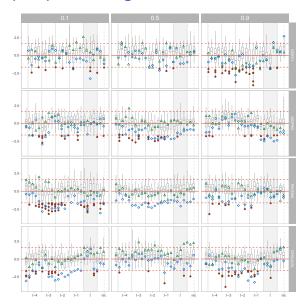


- QARX better than QAR in particular for low quantiles
- Economy and Output most relevant in for median and low quantiles
- Inflation and Financial sector selected for high quantiles

Out-of-sample quantile regression: RMSPE



Out-of-sample quantile regression: DM test



Conclusions

- Advanced NLP to extract economic sentiment from news
- Sentiment is useful in forecasting, while marginally in nowcasting
- Possible explanation: reporting of economic news is not only about the past events, but also discusses future scenarios
- Other works:
 - ► Explore the **narrative** aspect of our sentiment algorithm
 - Application to EU (translate news to English)
 - Compare with other approaches: EPU, LMD, ...

References

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Our working papers is available at:

 Barbaglia, Consoli, Manzan (2020) "Forecasting with Economic News" Available at SSRN: https://ssrn.com/abstract=3698121

Sentiment analysis: benefits and costs

Advantages

- easy to interpret and create a narrative
- ullet sentiment is expressed as a number in [-1,1]

Disadvantages

- the set of rules mapped by the algorithm is limited
- this approach works only with the English language
 - ightarrow we rely on the machine learning $\it{eTranslation}$ service by the European Commission





World Bank Ontology

Selection of economic synonyms of an economic concept with SPARQL queries on the World Bank Group Ontology³:

- Classification schema of economic concepts to describe and link language and terminology
- Concepts are stored and linked in a logical hierarchy and can relate across subject areas

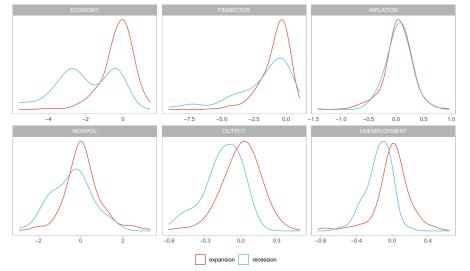
For instance, Industrial Production:

⇒ manufacturing; industrial output; secondary sector; industry productivity; manufacturing development; industrial growth; manufacturing productivity ...



³http://vocabulary.worldbank.org/thesaurus.html

Kernel density of the economic sentiment measures







In-sample Lasso variable selection

