Sentiment and Uncertainty indexes to Forecast the Italian Economic Activity¹

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¹The opinions expressed are those of the authors and do not reflect the views of the Bank of Italy or the Eurosystem.

Motivation

Forecasting faces new hard challenges

- Macroeconomic facts have been changing rapidly (Ng, and Wright, 2013)
- Legacies of the latest deep recessions

But...

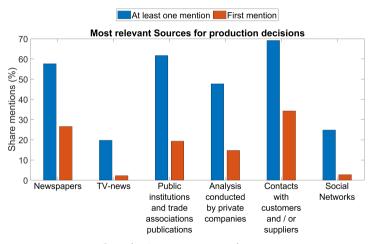
- Big data availability
- Novel sources of unstructured, high-dimensional, high-frequency and timely information

Our contribution

- Build Sentiment Indicators (TESI) and Uncertainty indicators (TEPU) for Italy from newspaper articles at high frequencies and for different sectors and topics (multi-source)
 - Italian businesses gather information to form their decisions from newspapers
- Use TESI and TEPU to track the short-term evolution of the Italian economic activity (monthly)
- Huge benefits in forecasting when used to build a high-frequency nowcasting indicator (weekly)

Motivation: Survey on most relevant source of information

Bank of Italy's Survey on Inflation and Growth Expectations



Sample size: 1199 respondents.

Text as Data

- Growing literature exploring the media-economy-opinion nexus
- Shapiro et al. (2018), Gentzkow et al. (2019), Thorsrud (JBES, 2020), Kalamara et al. (BoE WP 2020), Ardia et al. (IJF, 2019), Algaba et al. (JES, 2020), Nguyen and La Cava (RBA WP 2020), Garboden (2019), Rogers and Xu (FRB WP 2020)
 - Economic perceptions affect policy preferences but these perceptions are oftenly driven by factors other than the economy, including media [Soroka et al. (2015)]
 - Newspapers catch the mood (and to a certain extent they amplify and propagate pessimism or optimism)
- Unstructured information: transforming text into numerical data (tokenization)
- Documents are not a simple sum of words (*The Library of Babel* by Jorge Luis Borges): extracting the meaning of the sentence

Factiva's repository

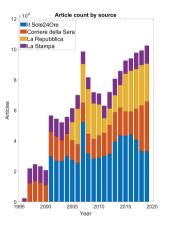
HTML Screenshot

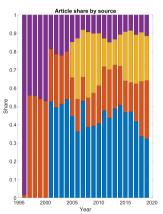


We downloaded approximately 2 million newspaper articles in the Italian language related to economic news from September 1996 to December 2019.

The News Corpus

Number of articles by year and source and share of articles for each source in each year





Data treatment - Sentiment & Uncertainty

• Pre-processing (removal of stop-words, non-meaningful punctuation, etc.)

Examples

Production fell by 1.2% overall between January and October. \rightarrow Production fall overall January October \rightarrow SENT $_t = -0.2$

- Building a meaningful dictionary related to economic topics in Italian (unigrams + n-grams)
 - Polarity (+/-) & weight (#)
 - Valence Shifters tailored to newspapers' jargon
- Constructing sentiment score for article j as \Rightarrow $SENT_{jt} = \frac{\sum_{i=1}^{No \ words} polarity_{ijt} \times shifter_{ijt}}{No \ words_{jt}}$

Examples

Gross Domestic Product has tallen \rightarrow SENT_t = -1.0

• Constructing also Economic Policy Uncertainty (EPU) Indicators as the share of articles containing at least an "Uncertainty" word

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Examples

Gross Domestic Product has fallen o SENT_t = -1.0

Istat's projections, GDP grew in 2019. Expansion is set to strengthen in 2020 \rightarrow SENT_t = 0.25

 Constructing also Economic Policy Uncertainty (EPU) Indicators as the share of articles containing at least an "Uncertainty" word

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Examples

Gross Domestic Product has fallen \to SENT $_t=-1.0$ Istat's projections, GDP grew in 2019. Expansion is set to strengthen in 2020 \to SENT $_t=0.28$

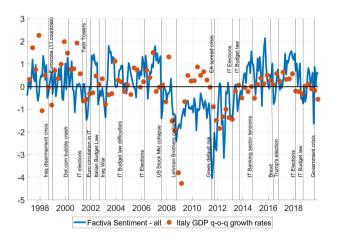
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Sentiment Index

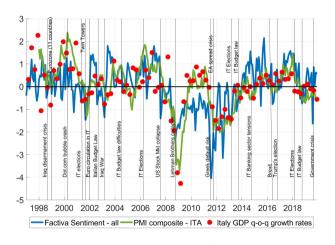
• Typically sentiment indices provided by statistical offices or PMIs are based on information collected up to the mid of the reference month.

• Sentiment based on newspapers' articles accounts for facts and events occurring daily.

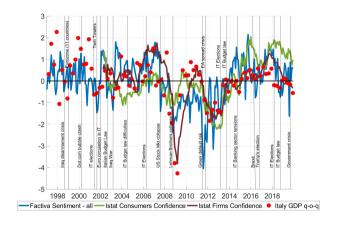
Sentiment Index and Economic Activity



Text-based Sentiment Index and PMI



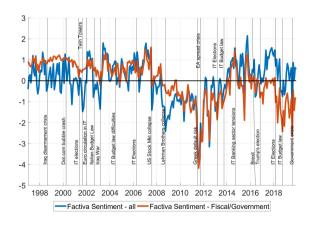
Text-based Sentiment Index and IESI (from NSI)



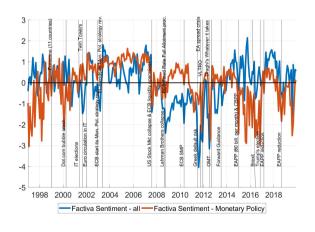
Sentiment Index - Taxonomy

- Sentiment by topics (# 15), grouping > 300 article pre-labeled categories
 - Fiscal Policy/Government
 - Monetary policy
 - Labor Markets
 - Economic conditions
 - Prices
 - Foreign Policy
 - ...
- Sentiment by sector (# 21)
 - Manufacturing
 - Services
 - Retail
 - ...
- 3 Sentiment Heterogeneity across newspaper sources (# 4)

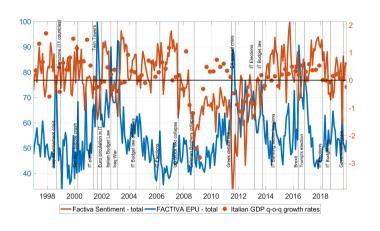
Sentiment index - by topics (Fiscal/Government)



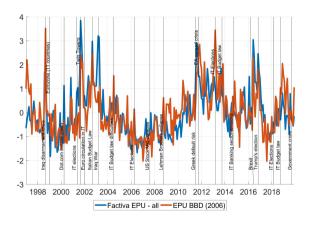
Sentiment index - by topics (Monetary Policy)



Economic Policy Uncertainty (EPU)



Economic Policy Uncertainty - Comparison with Bloom, Baker Davis (2016)



Empirical application #1 - Bayesian Model Averaging (BMA)

Short-term forecasting with monthly data

- Target. q-o-q growth of the Italian GDP and of its main demand/supply components
- Model/Method. Bayesian Model Averaging (BMA) (Bencivelli, Marcellino, and Moretti. EE, 2017)
- Data.
 - Baseline model: soft indicators (from business surveys and PMIs), industrial production index;
 - Augmented model: baseline + sentiment from newspapers' articles (overall index)
- Pseudo real-time forecasting exercise with monthly data
- Test the ability of **text-based indicators** (Sentiment and EPU) to forecast the Italian economic activity and its main components (T-model)

Empirical application - BMA Results on point forecasts

Short-term forecasting - Relative RMSFE for nowcasting and forecasting

• T-model tends to lower the RMSFE during the most turbulent period (2011-2014), in particular for HHC.

Table: Relative RMSFE for nowcasting (n) and forecasting (f)

| | 2011.1 - 2014.12 | | 2015.1 - 2019.12 | | 2011.1 - 2019.12 | |
|-----|------------------|------|------------------|------|------------------|------|
| | n | f | n | f | n | f |
| GDP | 0.93 | 0.91 | 1.17 | 1.16 | 1.00 | 1.00 |
| VAS | 0.97 | 1.21 | 1.08 | 1.08 | 1.00 | 1.00 |
| GFI | 1.03 | 0.94 | 1.13 | 1.08 | 1.03 | 1.00 |
| HHC | 0.83 | 0.79 | 1.46 | 1.29 | 0.99 | 1.00 |

Empirical application - BMA Results on density forecasts

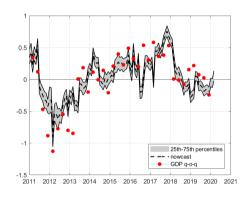
Short-term forecasting - Average log score based on WLRT (Amisano & Giacomini, 2007)

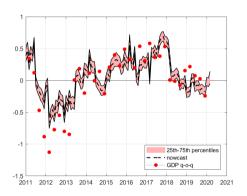
• T-model definitely outperforms the benchmark overall, and in particular during the sovereign debt crisis. Text-based indicators squeeze the uncertainty around nowcasts

Table: Average Log Score for nowcasting (n) and forecasting (f)

| | 2011.1 - 2014.12 | | 2015.1 - 2019.12 | | 2011.1 - 2019.12 | |
|-----|------------------|------|------------------|-------|------------------|------|
| | n | f | n | f | n | f |
| GDP | 9.1 | 8.6 | -15.6 | -22.4 | 6.1 | 6.6 |
| VAS | 5.3 | 6.6 | -7.1 | -10.3 | 3.7 | 6.4 |
| GFI | 3.6 | 23.7 | 6.9 | 10.5 | 4.6 | 24.5 |
| HHC | 14.6 | 12.2 | -9.4 | -11.8 | 11.4 | 11.8 |

Nowcast of GDP qoq

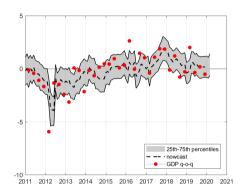




T-model

Baseline

Nowcast of GFI qoq

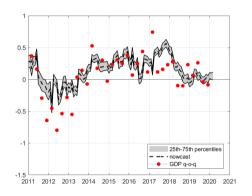


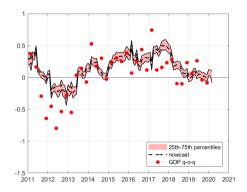
25th-75th percentiles - -- · nowcast 2012 2013 2014 2015 2016

T-model

Baseline

Nowcast of VAS qoq

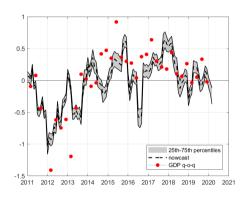


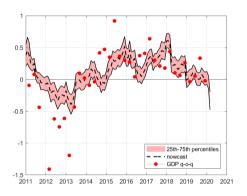


T-model

Baseline

Nowcast of HHC qoq

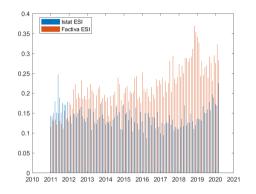


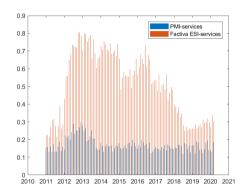


T-model

Baseline

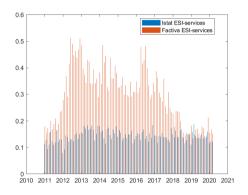
Posterior Inclusion Probabilities for GDP qoq Nowcasts

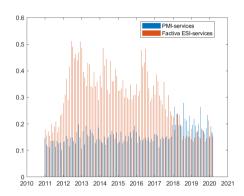




• PIP measures relative importance of each regressor to explain the variance of the target variable. SI is picked more frequently than PMI or Istat ESI.

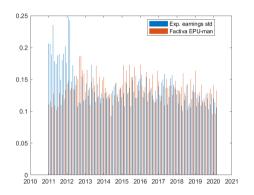
Posterior Inclusion Probabilities for VAS gog Nowcasts

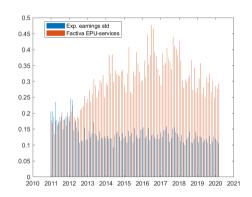




• SI for Services is picked more frequently the corresponding PMI or Istat SI.

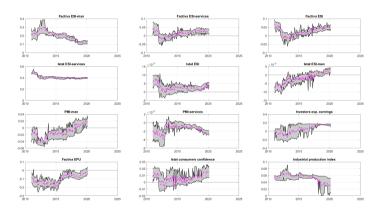
Posterior Inclusion Probabilities for GFI qoq Nowcasts





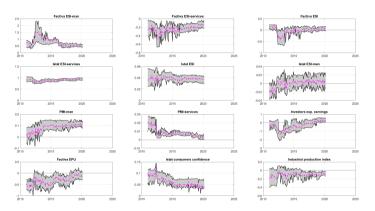
• EPU for Services is picked more frequently the std. dev. of expected earnings.

Regression Coefficients and 25th-75th percentiles for GDP qoq Nowcasts



- TESI and TEPU have expected sign.
- TESI-manufacturing and TEPU outperform.

Regression Coefficients and 25th-75th percentiles for GFI qoq Nowcasts



- SI and EPU weigh more than Istat ESI and PMI with expected sign.
- Text-based SI for Manufacturing outperforms. EPU negative contribution as expected.

Empirical application - A Weekly economic indicator

Following Stock and Watson (2002) and Lewis, Mertens and Stock (2020), we build a weekly indicator of economic activity

Explore the role of information timeliness

We find that

- ullet TESI and TEPU help nowcast the GDP (RMSFE reduced by 15-17% from baseline)
- Gains seem due to
 - Better tracking than other weekly variables
 - More timely tracking than monthly indicators
- CSSED analysis shows stable gains over most of the out-of-sample period

The model

We extract the first Principal Component from two different sets of variables:

- Group 1 (baseline)
 - Electric Consumption, Expected Earnings std (weekly)
 - PMI indices, ISTAT sentiment (monthly, inferred weekly)
- Group 2 (factiva)
 - Dabatase 1
 - TESI and TEPU indicators (weekly)

We use it to nowcast GDP growth yoy

• Using only pseudo real-time available data

The model

• We regress GDP yoy variation available at week τ against the 13-periods-average of the first PC.

At week t (today) call $T_t < t$ the week at which the latest data is available.

$$\Delta Y_{(yoy),\tau} = \alpha_{T_t}^i + \beta_{T_t}^i \tilde{X}_{\tau}^i + \varepsilon_{\tau}, \quad \tau = t_0, t_0 + 1 \dots, T_t$$
$$\tilde{X}_{\tau}^i = \frac{1}{13} \sum_{s=\tau-12}^{\tau} X_s^i$$

• At week t, compute the index for each past period $\tau \leq t$ using estimate coefficient

$$\Delta \hat{Y}_{(yoy),t}^i = \alpha_{\tau}^i + \beta_{\tau}^i X_t^i$$

Forecasting error

• Compute the nowcasting errors by using the ex-post available data on GDP as

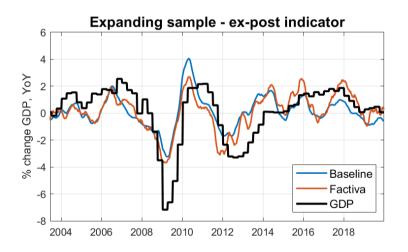
$$E_t^i = \Delta Y_{(yoy),t} - \Delta \hat{Y}_{(yoy),t}^i$$

- ullet pprox 13 nowcasts per quarter
- We find large gains on weekly nowcasts when adding Sentiment and EPU indicators

Table: Relative RMSFE

| | Expanding | Rolling (335 weeks) |
|--------------|-----------|---------------------|
| All sample | 0.85 | 0.83 |
| Negative GDP | 0.88 | 0.96 |
| Positive GDP | 0.82 | 0.75 |

Weekly indicator: last vintage



Wrap-up

- We developed an Italian economic dictionary with polarity and shifters
- We used Factiva newspapers data to estimate Sentiment and EPU indices at daily and weekly frequencies
- We evaluated their properties in two short-term forecasting exercises
 - Monthly: point-forecast gains in recessions; large density forecast gains overall
 - Weekly: large point-forecast gains across all the sample
- Results seem quite promising
- Further developments:
 - Extend exploration of high-frequency properties and corresponding gains
 - Explore deep learning techniques to handle text data and weight our dictionary

