

Universität St.Gallen

Can We Predict Business Cycles With Natural Language Processing?

Exploring the Meaning of Boom and Bust

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Presentation for the Annual Congress of the Swiss Society of Economics and Statistics (SSES/SGVS)

November 11, 2021

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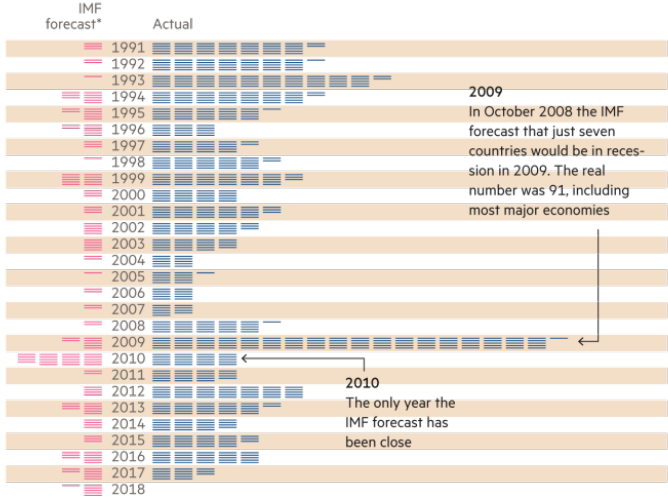
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Countries in recession

Each mark represents a country



* Made in October of previous year

Source: IMF

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Research Problem and Opportunity

Substantial efforts dedicated to predicting key macroeconomic variables, yet ...

- It is difficult to predict crises: Brigden (2019) has found that IMF macroeconomic projections correctly predicted only 4 out of 469 recessions in 194 countries.
- Common business cycle indicators do not use text analysis despite its potential (new insights into agents' expectations, high-frequency of text data).

Current literature establishing connection between text corpora and macroeconomic variables

1. Custom Dictionary Methods: Baker, Bloom, and Davis (2016), Nyman et al. (2018)
2. Topic Modelling and Sentiment Analysis: Larsen and Thorsrud (2019), Thorsrud (2020), Azqueta-Gavaldón, Hirschbühl, Onorante, and Saiz (2020)

These recent attempts at using text analysis to nowcast or forecast macroeconomic variables use bag-of-words techniques and thus entirely **disregard context and word ordering**.

The Purpose

Emphasise the value and importance of context and meaning for textual analysis in macroeconomics.

My contribution:

- Create a real-time text-based index of *macroeconomic sentiments* exhibiting (at least some of these) useful properties
  - i) stable relationship to macroeconomic variables,
  - ii) predictive power towards GDP / general macroeconomic conditions,
  - iii) predictive power towards business cycle turning points

Final product: The Relative Sentiment Index

An index tracking *macroeconomic sentiments* based on computationally inferred meaning of key business cycle terms.

Context and Meaning in Computational Linguistics

The Distributional Hypothesis

> *You shall know a word by the company it keeps.*
>
> — Firth (1957, p. 179), *A Synopsis of Linguistic Theory*

Implication 1: A word's meaning can be described by a probability distribution over its context words.
Implication 2: If a pair of words has a high *relative* co-occurrence probability, these words should have similar meanings.

In order for computer to understand meaning it needs to learn about co-occurrence probabilities of words.

Examples:

- *severe* and *crisis* vs. *severe* and *prosperity*
- *sustainable* and *recovery* vs. *sustainable* and *depression*

Text Corpora

Corpus I. (Business Cycle News):
Purpose: Insights into how agents think about business cycles

Search Query: Economy/Economic + "Business Cycle Words" (in heading/first paragraph, close to each other)
Newspapers: NY Times, Washington Post, The WSJ, USA Today, The Guardian, The Times, FT, Reuters
Time Span: 01/1990 – 04/2020
Number of Articles (Unique Words): 61 675 (278 470)

Corpus II. (Economic Expectations News):
Purpose: Proxy beliefs about future economic outcomes

Search Query: Economy/Economic + "Forward-Looking Words" (in heading/1st paragraph, close to each other)
Newspapers: NY Times, Washington Post, The WSJ, USA Today, Reuters
Time Span: 09/1987 (01/1990) – 04/2020
Number of Articles (Unique Words): 31 259 (146 639)

Search Query Words Examples

- Business cycle words (14): expansion, contraction, crisis, depression, prosperity...
- Forward-looking words (67): expectation, prediction, forecast, ...

Methodology
The Relative Sentiment Index

I. Collect News Articles and Represent in Matrix → II. Infer Meaning → III. Examine Euclidian Space

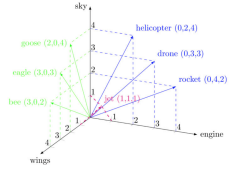
- Word-Word Co-Occurrence Matrix

$$X = \begin{array}{c} \\ I \\ like \\ enjoy \\ deep \\ learning \\ NLP \\ flying \\ . \end{array} \begin{array}{c} \begin{array}{cccccccc} I & like & enjoy & deep & learning & NLP & flying & . \end{array} \\ \begin{bmatrix} 0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

- GloVe: Global Vectors for Word Representation (Pennington, Socher, & Manning, 2014)
- Other algorithms out there: BERT, Word2Vec, Sent2Vec, etc.
- Dimensionality reduction and stochastic gradient descent filter out "patterns" in language

$$F(\mathbf{w}_i, \mathbf{w}_j, \tilde{\mathbf{w}}_k) = \frac{P_{ik}}{P_{jk}}; \quad P_{ik} = \frac{X_{ik}}{X_i}$$

- Locate Contractionary and Expansionary Positions
- Word vectors are "meaningful": Use their properties
- Examples:
  suprime + *lending* ≈ *mortgage*
  yellen − *fed* + *ecb* ≈ *trichet*



Methodology
The Relative Sentiment Index

IV. Find Similar Words: Expansionary and Contractionary Vocabulary

- Once the expansionary and contractionary vectors have been located: Find most similar word vectors
- Use proximity metric: Cosine Distance

$$cos(\theta) = \frac{\sum_{i=1}^{n} u_i v_i}{\sqrt{\sum_{i=1}^{n} u_i^2} \sqrt{\sum_{i=1}^{n} v_i^2}}$$

V. Count: Create Index

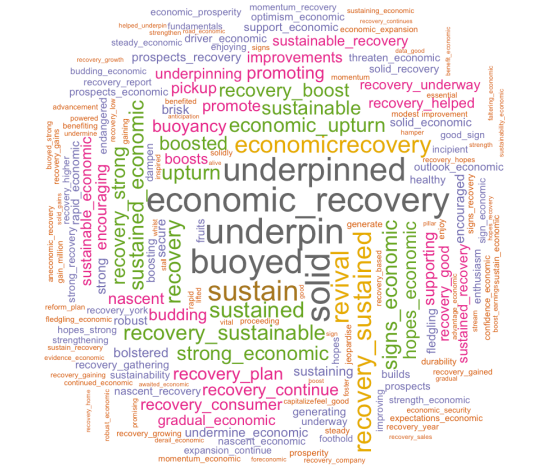
- Calculate proportion of words in articles from the respective vocabulary per time period (month)
- Create Expansionary and Contractionary Sentiment Time Series
- Difference: Expansionary - Contractionary = Relative Sentiment Index

VI. Analyse Properties

- Time Series Patterns
- Simple Linear Regressions
- Granger-Causality Tests
- Structural Breaks

Expansionary and Contractionary Words

Size by cosine distance from expansionary and contractionary positions.



Expansionary Vocabulary



Contractionary Vocabulary

Results: Relative Sentiment Index

Interesting Patterns

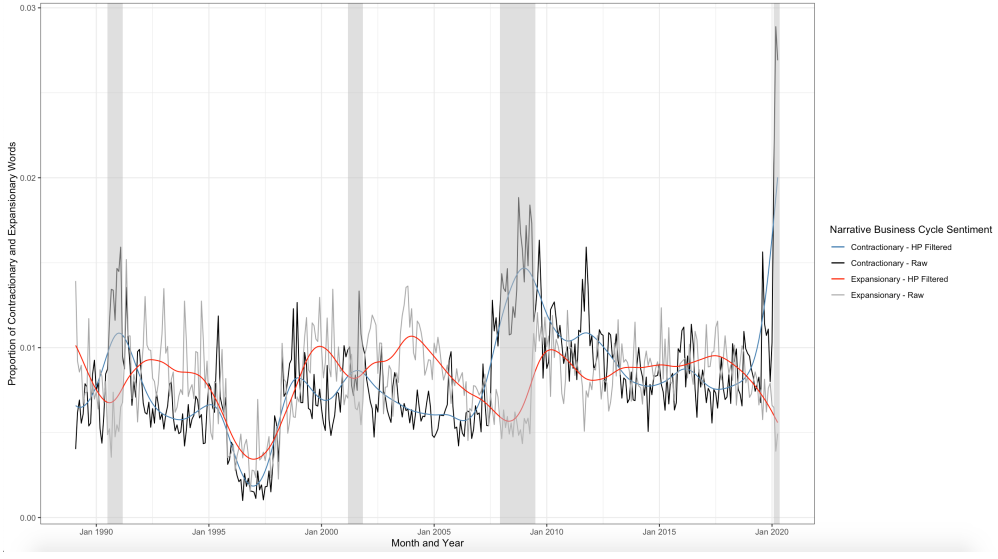


Figure: Business Cycle Sentiment: Expansionary and Contractionary

Results: Relative Sentiment Index

Interesting Patterns

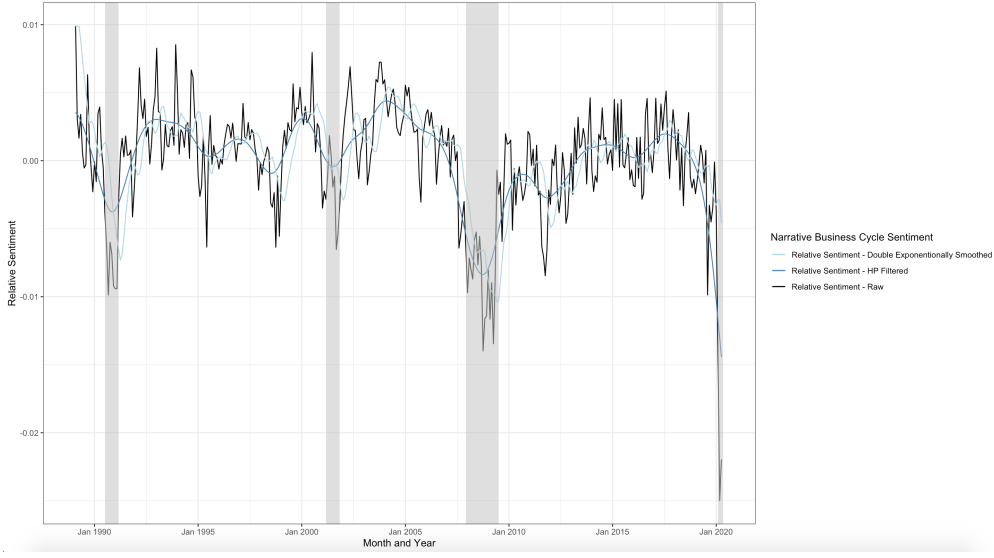


Figure: Relative Cycle Sentiment (RS_t) Index

Results and Evaluation: Relative Sentiment Index

Does the Relative Sentiment Index lead or lag macroeconomic variables?

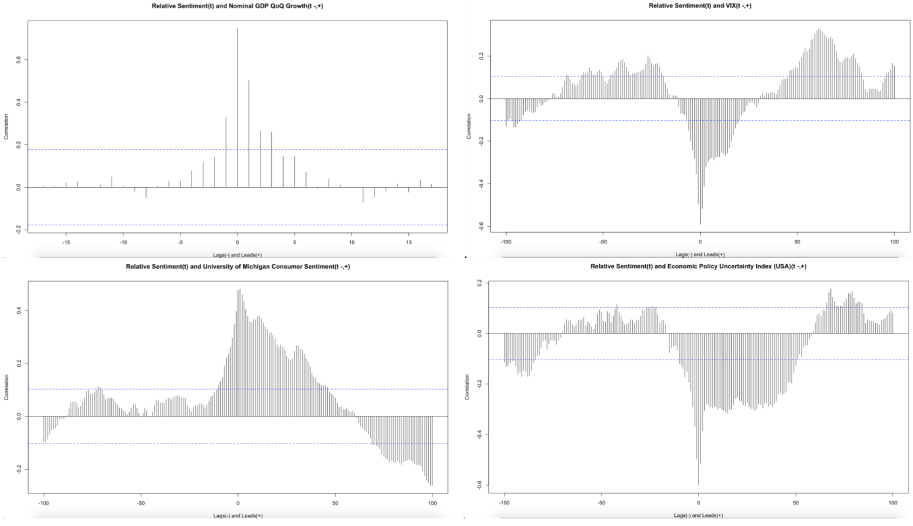


Figure: Cross-Correlation Functions: Relative Sentiment with U.S. GDP Growth, VIX, UoM Consumer Sentiment Survey, Economic Policy Uncertainty

Results and Evaluation: Relative Sentiment Index

Do other indices lead or lag macroeconomic variables?

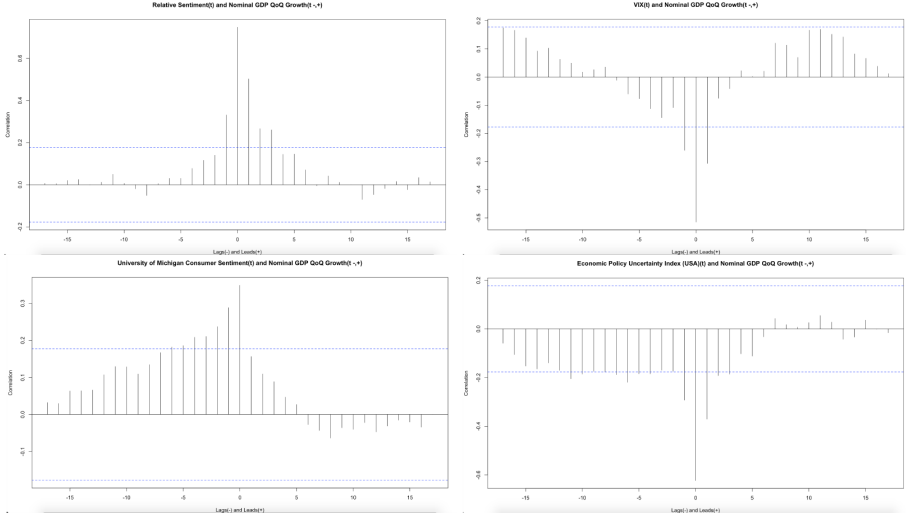


Figure: Cross-Correlation Functions: Other Indices with U.S. GDP Growth, VIX, UoM Consumer Sentiment Survey, Economic Policy Uncertainty

Results and Evaluation: Relative Sentiment Index

Is the Relative Sentiment Index useful in predicting macroeconomic variables?

Table 8: Granger Causality: Constructed Series → Comparative Series

Granger Causality: Constructed Series → Comparative Series					
Series	GDP, nom, QoQ, growth	GDP, real, QoQ, growth	VIX	UMCSENT	EPU
Relative Sentiment	19.8^{***} $(8.5 * 10^{-6})$	15.4^{***} $(8.9 * 10^{-5})$	13.3^{*} (0.065)	30.9^{***} $(2.6e-05)$	32.4^{***} (0.0002)
Entropy	0.41 (0.52)	0.2 (0.65)	0.39 (0.94)	0.23 (0.89)	8.3^{*} (0.08)

Table 9: Granger Causality: Comparative Series → Constructed Series

Granger Causality: Comparative Series → Constructed Series		
Time Series	Relative Sentiment	Entropy
GDP, nominal, QoQ Growth (U.S.), quarterly	1.2 (0.27)	0.12 (0.73)
GDP, real, QoQ Growth (U.S.), quarterly	3.2^{*} (0.075)	0.003 (0.95)
VIX (CBOE Volatility Index), monthly average	21.5^{***} (0.003)	2.6 (0.46)
University of Michigan Consumer Sentiment (UMCSENT)	8.4 (0.21)	0.14 (0.93)
Economic Policy Uncertainty (EPU), U.S., monthly	30.5^{***} (0.0004)	1.7 (0.8)

Figure: Granger-Causality Tests: Method from Toda and Yamamoto (1995)

$$GDP_t = c_1 + \alpha_1 GDP_{t-1} + \alpha_2 GDP_{t-2} + ... + \alpha_p GDP_{t-p} + \beta_1 RS_{t-1} + \beta_2 RS_{t-2} + ... + \beta_p RS_{t-p} + \epsilon_t$$
$$RS_t = c_2 + \gamma_1 GDP_{t-1} + \gamma_2 GDP_{t-2} + ... + \gamma_p GDP_{t-p} + \delta_1 RS_{t-1} + \delta_2 RS_{t-2} + ... + \delta_p RS_{t-p} + \epsilon_t$$

Results and Evaluation: Relative Sentiment Index

Does the Relative Sentiment Index exhibit structural breaks pre-business-cycle turning points?

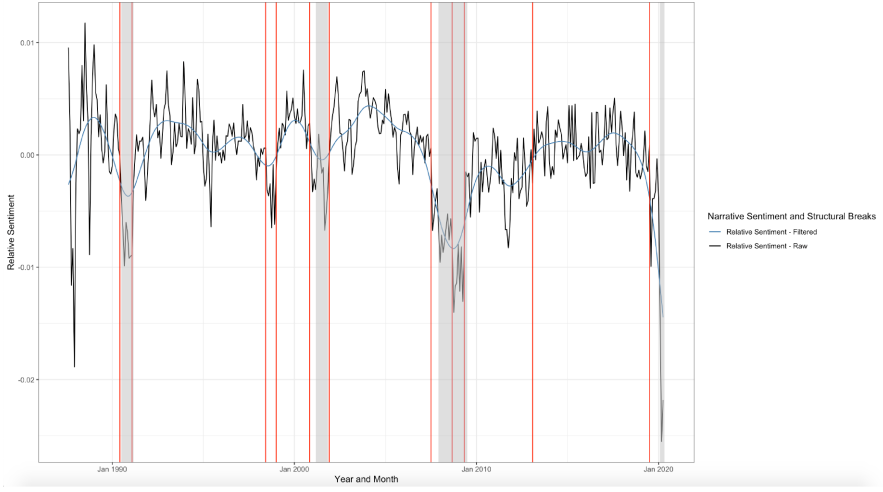


Figure 17: Monthly Optimal Estimated Structural Breaks (BIC chosen model) – Red Colour

Figure: Structural Breaks for RS_t Index. According to Bai and Perron (2003).

Conclusions

Relative Sentiment Index

- Stable Relationship to Macroeconomic Data
- Predicting GDP / General Macroeconomic Conditions
- Predicting Business Cycle Turning Points

} Evidence of all three

Limitations:

- More robustness checks necessary.
- For a credibly predictive index (out-of-sample testing), I would either need time-dependent lexicons or only use an early subset of articles to estimate the word embeddings.
- Need more news articles.

Perspectives: Further Research

There are many ways my work could be extended and/or improved

- Use more/different insights from the trained vectors.
- Make the (word) vectors supervised.
- Make the vectors time-variable.
- Use other word/sentence/document-vectorisation techniques.
- More news articles.

There are many opportunities for further research with word embeddings and vectorisation techniques.

Text Embeddings: A Step Towards Economic Narratives?

We need to capture meaning to find economic narratives. A narrative can be defined as:

> *An account of a series of events, facts, etc., given in order and with the establishing of connections between them; a narration, a story, an account.*
>
> *A story or representation used to give an explanatory or justificatory account of a society, period, etc.*
>
> — Oxford English Dictionary (2003), *Definition 1 and 2*

Implication 1: Need to account for *order* and *connection* between words to find (economic) narratives.

Implication 2: Need to account for *context* and *meaning* behind words to find (economic) narratives.

Thank You for Your Attention!

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