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Economic uncertainty and natural language processing; the case of Russia

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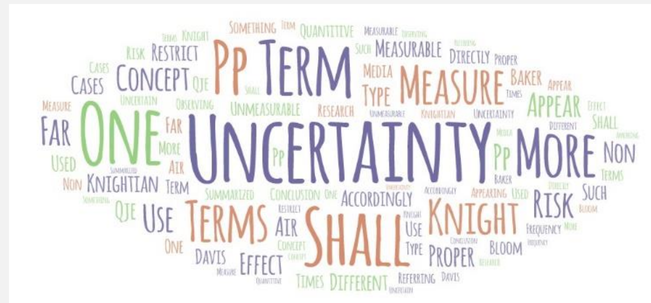

Based on paper: *Economic Analysis and Policy* 73 (2022), 564-562

90th East Jour Fixe of the Oesterreichische Nationalbank (OeNB)

Vienna, 4 October 2022

This research has been financed by the National Science Centre in Poland Opus 8 project 2018/29/B/HS4/01462, *Construction and testing of country-specific measures of economic uncertainty*

The aims of the research

To introduce and test a new method of constructing text-based economic policy uncertainty indices suitable for countries with media publications ('texts') published in languages other than English.

This presentation discusses results for Russia, but we have analogously constructed uncertainty indices for Belarus, Kazakhstan and Poland.

Main messages

Constructing text-based country-specific uncertainty indices should consider linguistic undertones and sentiments.

The application of the approach developed for English-language text-based uncertainty indices, in its original form, does not work well for non-English texts.

An application of simple and well-rehearsed natural language processing methods helps.

Country-specific uncertainty indices have

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1. Constructing text-based country-specific uncertainty indices should consider linguistic undertones and sentiments.
2. The application of the approach developed for English-language text-based uncertainty indices, in its original form, does not work well for non-English texts.
3. An application of simple and well-rehearsed natural language processing methods helps.
4. Country-specific uncertainty indices have ***predictive power in forecasting real effects*** if properly constructed.

Digression: traditional text-based measures of EPU (BBD, 2016, *QJE*)

Step 1: Define the sets of ***descriptors*** of interest;

e.g., for EPU: {economic}, {policy}, {uncertainty}.

Step 2: Search all the articles in the database (corpus) to identify those that contain at least one word from each set of descriptors {economic} AND {policy} AND {uncertainty}.

That is, the article i is selected if

$$I_i = I_{\{economic\}i} \times I_{\{policy\}i} \times I_{\{uncertainty\}i} = 1$$

Step 3: Do some checking (human validation) to determine whether the selected article's topic is indeed related to economics.

Step 4: Aggregate and scale the frequencies of selected articles.

Why a new method?

Traditional methods based on English-language texts:

1. Rely on *human validation* of topics of articles for checking whether the selected article has economic context.

   '*Considering the economic aspect of sales, we have a policy of reducing prices of tyres for which we are uncertain that they can maintain the desired air pressure for more than two years*'.

2. *Ignore undertones and emotions* of words or phrases, which are typical for numerous other languages and reporting styles.

The first one is *costly*, particularly if applied to a variety of languages.

The second one is *imprecise and prone to bias*.

Techniques applied (new and old)

- *Natural language processing* methods:

  Word2vec, to define descriptors (in Step 1).

  Latent Dirichlet Allocation, which defines predominant topics of articles to identify those related to economics (in Steps 2 & 3, validation).

- *Sentiment weighting* (lexicon-based): to account for language-specific undertones and emotions (in Step 4, aggregation).

- *Events Valuation Assessment* (EVA): for checking the validity of results (matching changes in indices with economically and politically relevant events).

- *Impulse response* (by local projection, Jordà, 2005, AER): confirming the theory that uncertainty has a predominantly negative effect on the real sphere (see, e.g. Bloom et al., 2018, *Ecnm*).

The NLP methods in brief

Word2vec: concept of *cosine similarity*.

This is a two-layer neural net that processes text. Its input is a text corpus, and its output is a set of symbols of 0-1 vectors: feature vectors for words in that corpus.

The most famous example is: "king"-"man" +" woman" =" queen".

LDA:

(a) Using all words from all articles in the database (the corpus), allocate words to topics, initially randomly.

(b) Iterate, until conformity with the Dirichlet distributions of words for topics and topics in articles, is reached.

These are not the newest methods but are well-rehearsed and widely validated.

Newer methods: e.g. ELMo or GloVe as an alternative to Word2vec and, e.g. neural topic modelling (Wang and Yang, AISTATS, 2020) as an alternative to LDA and are not yet fully checked for economic text analysis.

Weighting by sentiments (lexicon-based)

Lists of words reflecting positive and negative sentiments are available in *sentiment lexicons*. For Russian: RuSentiLex (Loukachevitch and Levchik, 2016, *LREC*).

For each article selected i, we compute fractions of positive and negative words and re-scale them, getting scaled fractions S_i^+, and S_i^-.

The *negative* sentiment-weighted selected frequency is:

$$I_i^S = I_i \times \omega_i \quad \text{, where } \omega_i = 1 + S_i^- \quad ,$$

where: $$I_i = I_{\{economic\}i} \times I_{\{policy\}i} \times I_{\{uncertainty\}i} = 1$$

Why do we use lexicon-based approach rather than the machine-learning?

e.g. BERT (see Devlin et al., 2019, *Ass. Comp. Ling. Proc.*)?

For some languages, particularly with complex conjugation (e.g. Slavic languages) the lexicon-based approach often gives comparable, if not better, results than BERT (Kotelnikova et al., 2021, *arXiv*).

Empirical results for Russia

- Uncertainty indices are constructed using data from 4 daily newspapers available electronically (1992-2018, over 1.1 million articles).
- Using Word2vec, we constructed descriptors of 30 or 50 words (depending on the newspaper) of {economic}, {policy} and {uncertainty}.
- Using LDA, we identified 20 topics, from which we eliminated topics identified as 'sport', 'fashion', 'culture', etc.

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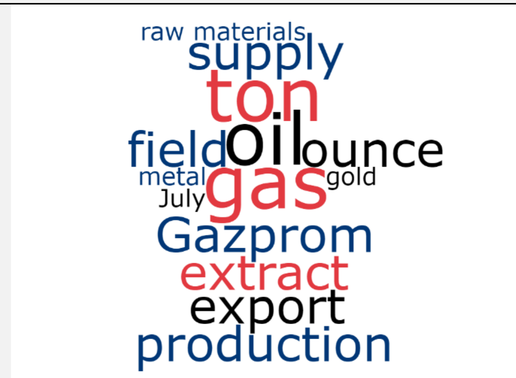
Distributions of words (stems) in sample topics, after translation

Commodities & markets

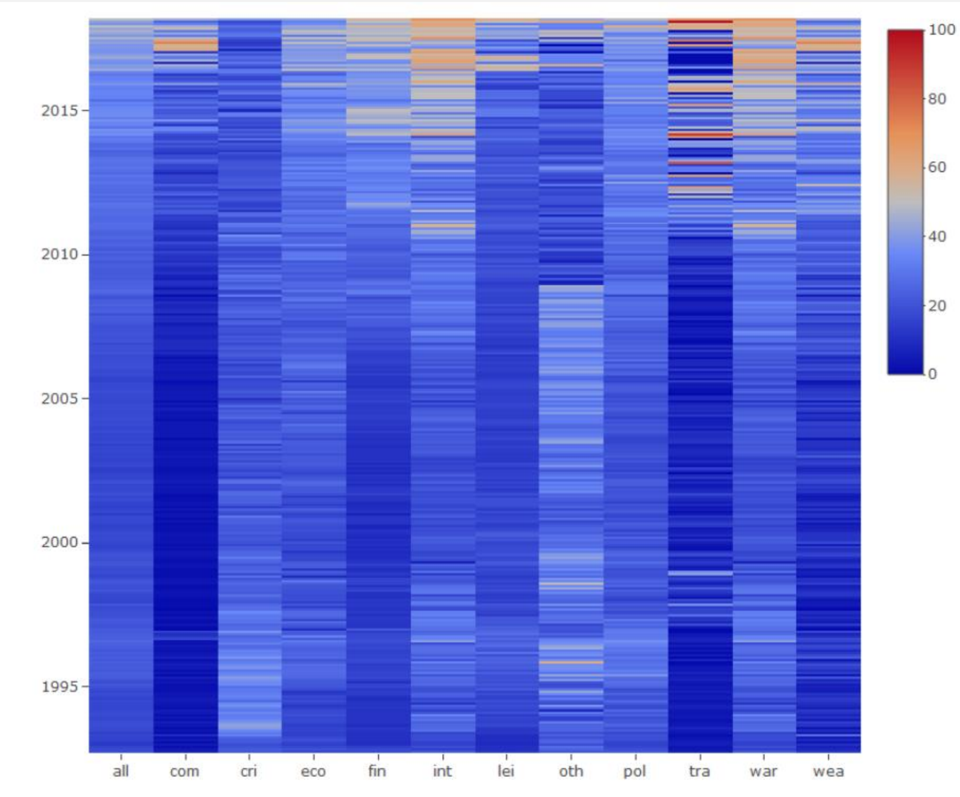
Finance & banking

Culture

Commodities



Monthly percentages of the appearance of {uncertainty} descriptors in *Kommersant*, Oct 1992 – Feb 2018



Clear evidence of the increase in uncertainty-related texts since 2012, particularly in articles related to:

- *trade*
- *intnl. relations*
- *war*

EVA analysis (comparison of U and EPU-Russia)

- We identify 49 uncertainty-generating events from January 1994, to February 2018:

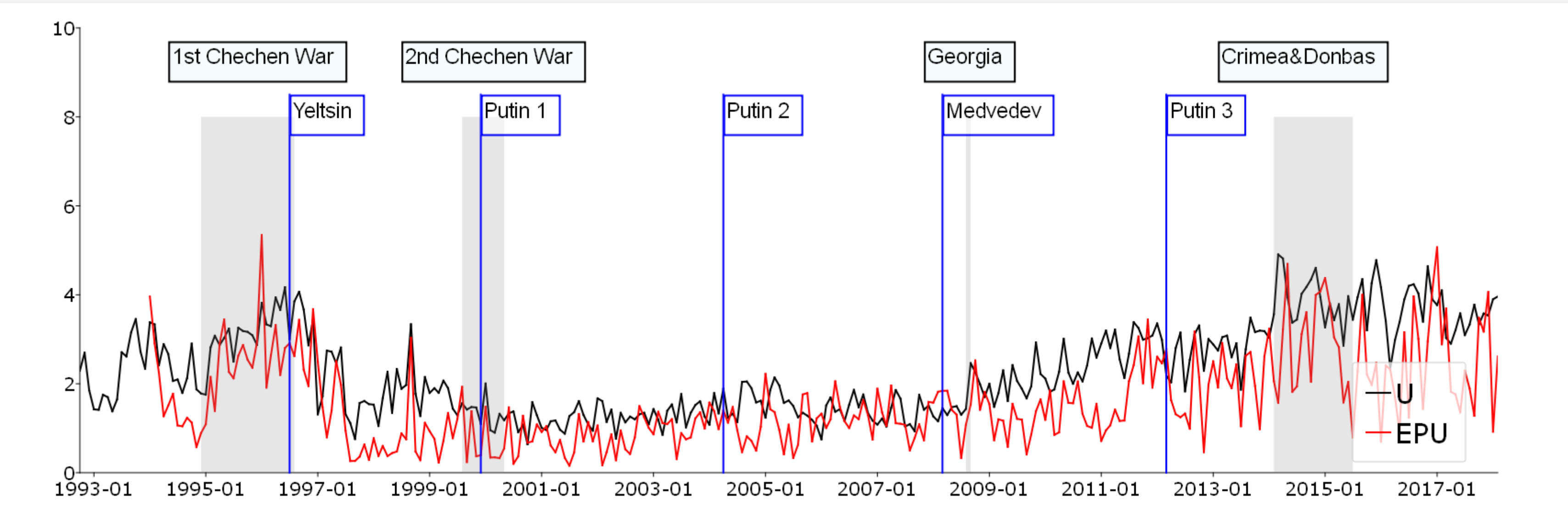
  -terrorist attacks or threats, natural or human-made disasters, politically motivated arrests and killings, border wars, military interventions, sudden economic policy changes like a devaluation, or international incident.

- We found 'peaks' of U and EPU-Russia (an increase over the previous month's value of more than 7.5%).
- We matched 46 peaks in the U series and 45 peaks in the EPU series with the pre-defined uncertainty-generating events.
- *This gives 92% accuracy for the match of peaks with events for U and 90% for EPU.*

Conclusion: both U and EPU-Russia are tracking the major uncertainty-generating events well, with U being slightly more accurate.

EVA analysis (comparison of U and EPU-Russia)

Comparison of the U and EPU-Russia uncertainty indices (divided by their standard deviations)



Source of data for EPU: https://www.policyuncertainty.com/russia_monthly.html

Real effect of uncertainty

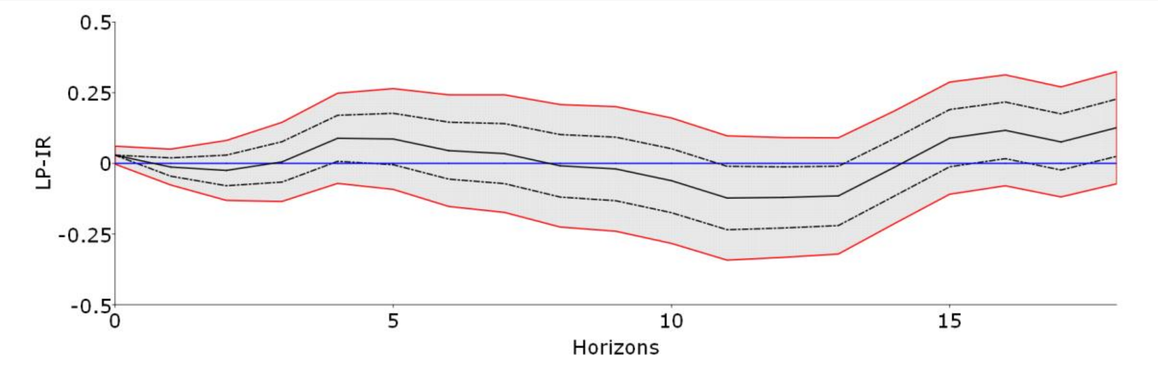
- Bloom *et al*. (2018) proved that there is a real ***negative*** effect of the first-order uncertainty shock.
- Are there real effects from uncertainty to a real variable in Russia?

The basic VAR model contains (all variables measured monthly):

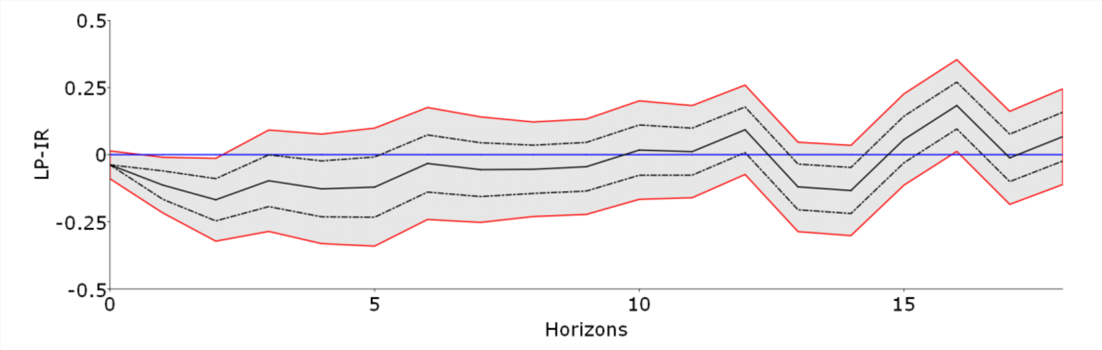
- Uncertainty measure;
- Brent oil price, deflated by the US CPI;
- Interbank interest rate (deflated by inflation), monthly data;
- Moscow stock market index (MOEX), in logs, deflated by CPI;
- Production output gap, measured by the log deviations from the Hodrick-Prescott trend.

Jordà linear projection impulse responses of industrial production in Russia to one standard deviation uncertainty shock

shock measured by EPU-Russia



shock measured by U



Some robustness analysis

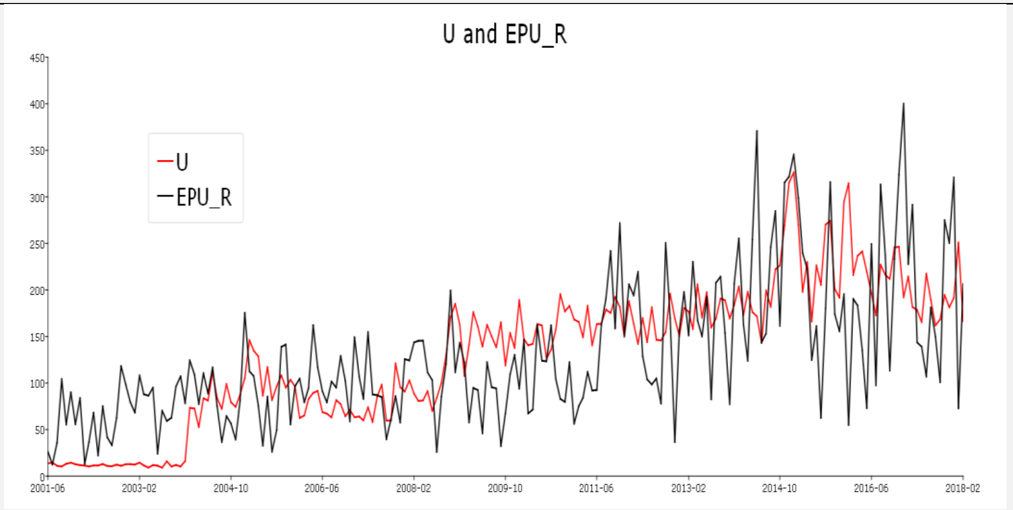
- Different VAR specifications used (with some variables removed).
- Similar results have been obtained for 12 variations of U (different measures of uncertainty, different Word2vec and LDA settings).
- Different methods of impulse response analysis Bootstrap-after-bootstrap bias correction of VAR parameters applied (Kilian, RES, 1998).
- Different Russian language lexicons used (e.g. Kaggle lexicon).
- Different formulae for the sentiment weights and scaling applied.

All these results *confirm* the results shown above.

Conclusions

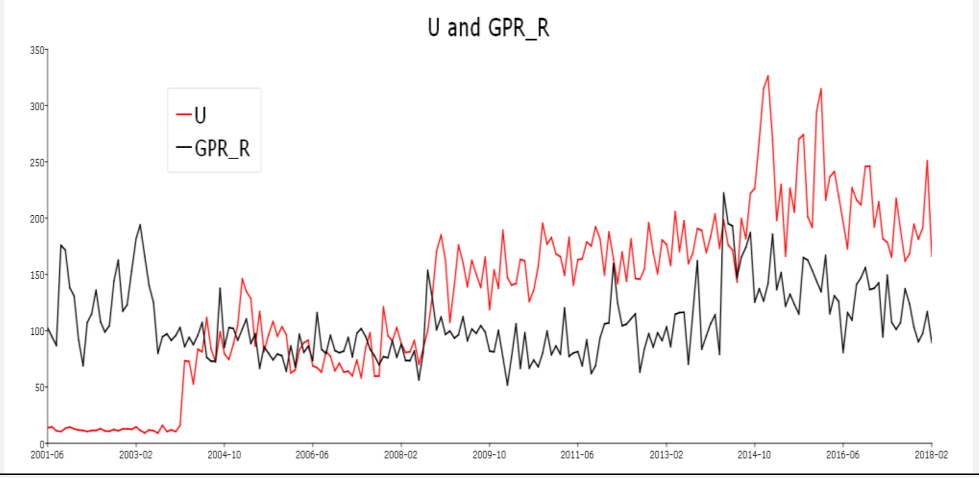
- The existence of the negative real effect of uncertainty has been confirmed, but only if U, not EPU, is used as a measure of uncertainty.
- Using machine learning tools can efficiently eliminate the need for human validation.
- Translating uncertainty-related words from English into local languages might blur the computed uncertainty measures.
- In the case of local language measures, there might be a linguistic identification problem between the 'uncertainty' and negative sentiments. This is clearly the case for Russia.
- It is room for more econometrics here. The fact that there are Bloom effects in industrial production does not necessarily mean that there will also be present in the quarterly GDP (mixed frequency VARs?).

Comparison of U with other uncertainty indices for Russia



EPU-R: BBD index for Russia, based on one Russian newspaper only (human validation, arbitrary selection of topics, no sentiment weighting).

Spearman corr. coeff: 0.64



GPR-R: Caldara & Iacoviello (2022, AER) index of geopolitical risk for Russia, One Russian newspaper (as BB&D, but with a different selection of words).

Spearman corr. coeff: 0.28