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Measuring Central Banks’ Sentiment and its Spillover Effects with a Network Approach

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Introduction

MOTIVATION

Central banking has changed dramatically throughout over the last 10-15 years, in particular since the Great Recession and the Covid-19 crisis.

- One of the most disruptive innovation has been the increasing use of **forward guidance.**

It has therefore become very important to assess the impact of **central banks' communication**.

LITERATURE

The academic literature has acknowledged that central banks' communication has an impact on the economy. It might be due to:

- **increase in transparency** (Acosta, 2015; Dincer and Eichengreen, 2014).
- **amount of information released** (Apel and Grimaldi, 2012).

However, **the interaction of central banks' communication has been less investigated.**

QUESTIONS

We apply text-sentiment analysis to a dataset comprising official documents from four central banks to answer these following questions:

1. **Does CBs' communication have an impact on financial variables?**
2. **How much CBs have been influencing each other through communication? Is it a time-varying effect?**

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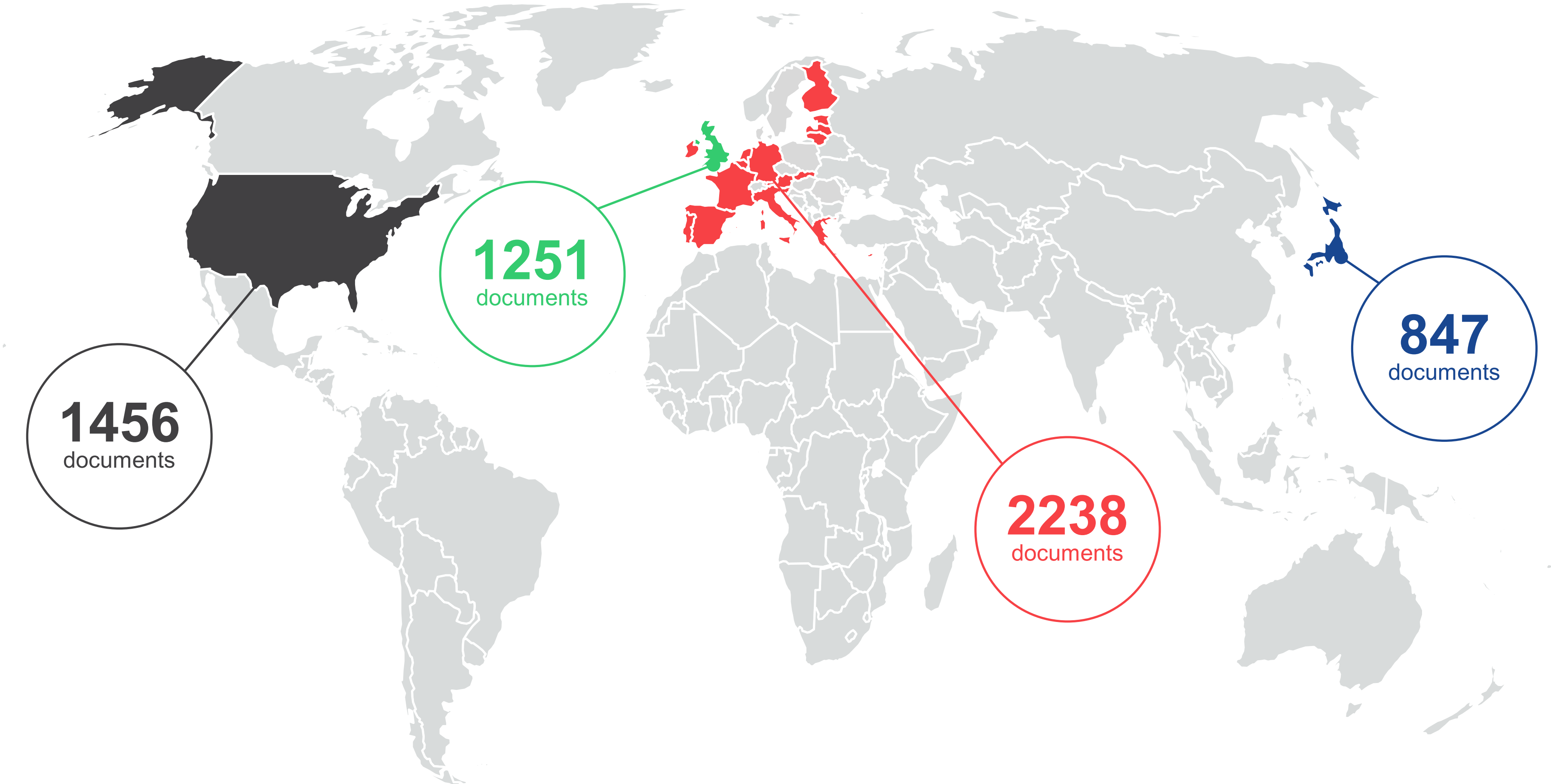
Data

We analyse documents from the Fed, ECB, BoE and BoJ



Sample period: from January 2000 to April 2020

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Data

A description of our database

The documents

- For each central bank we considered:
  - **top officials' speeches;**
  - **monetary policy press releases.**
- Speeches can vary in their format, whereas releases are shorter and standardized, as they are the communication of monetary policy decisions.

The database

- We downloaded documents from **the institutional websites** of each central bank.[1]
- More than one speech and release might have been published on the same day, leading to a potential distortion for the index computation.
- To overcome this issue, **we decided to merge documents with the same date** so to have a single value indicator for each publication date in the dataset.

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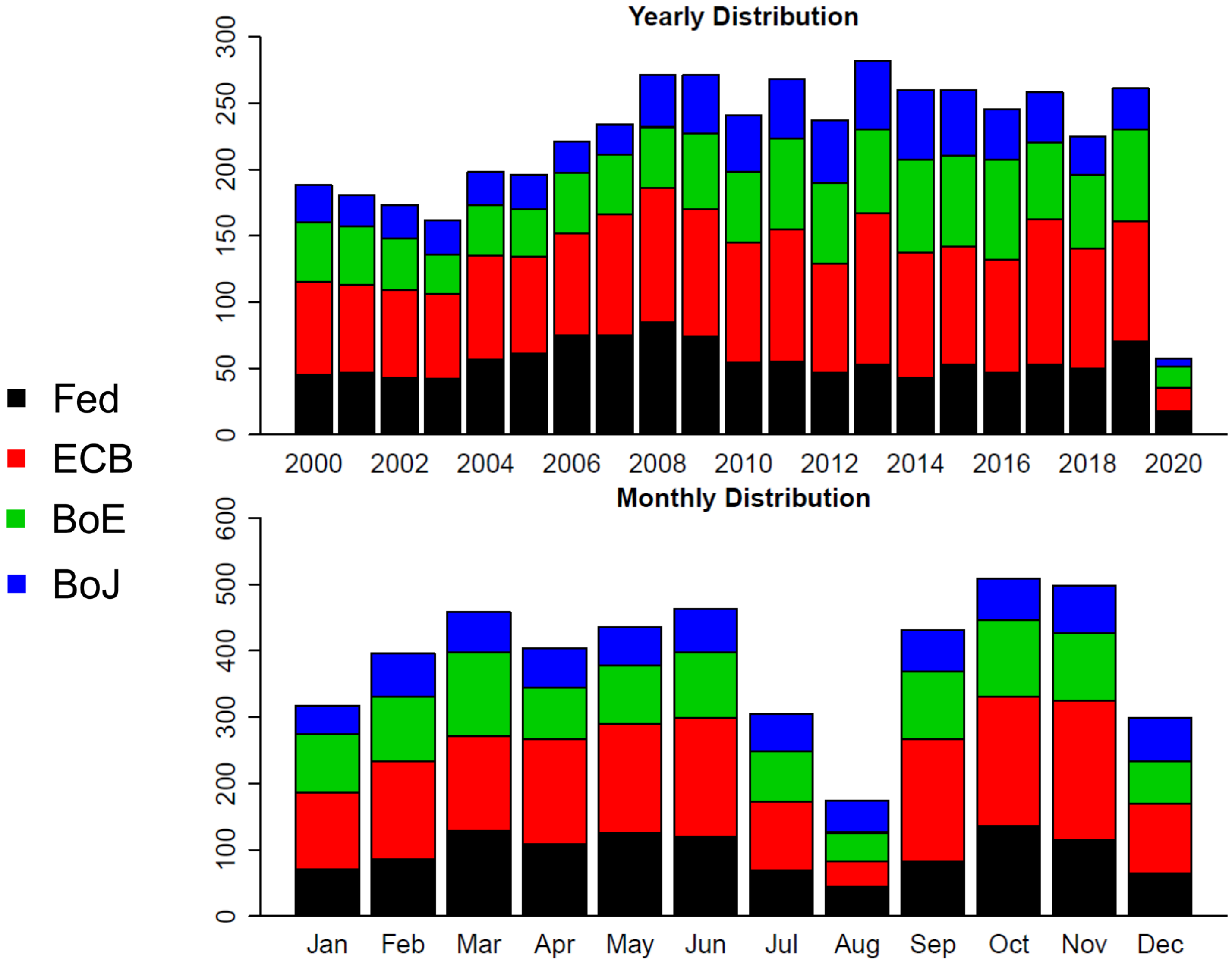
[1]For Fed monetary policy releases we utilized the database available on the website of the Federal Reserve Bank of St. Louis.

Data

A description of our Database[1]



[1]Since we merged documents with the same date, we show the distribution of days with a speech. E.g. if there are two documents for the same day, the counting is one.

Central Bank Sentiment Indexes

Methodology: text-sentiment analysis

Data Loading

Upload of «raw» data that can be manipulated through a software.

Parsing

We cleaned the text by converting it to lowercase and then removing numbers, extra spaces, punctuation and regular expressions (<^.?>*+\). **Conversion of the text into a «corpus».**

Tokenization

The text is categorized in blocks readable by the software and a stemming algorithm is applied, obtaining a **Document Term Matrix.**

Lexicon approach

We choose the **Loughran - McDonald (2011) dictionary**, matching words with positive/negative connotation for all the documents of each central bank (Shapiro and Wilson, 2019; Armelius et al., 2020).

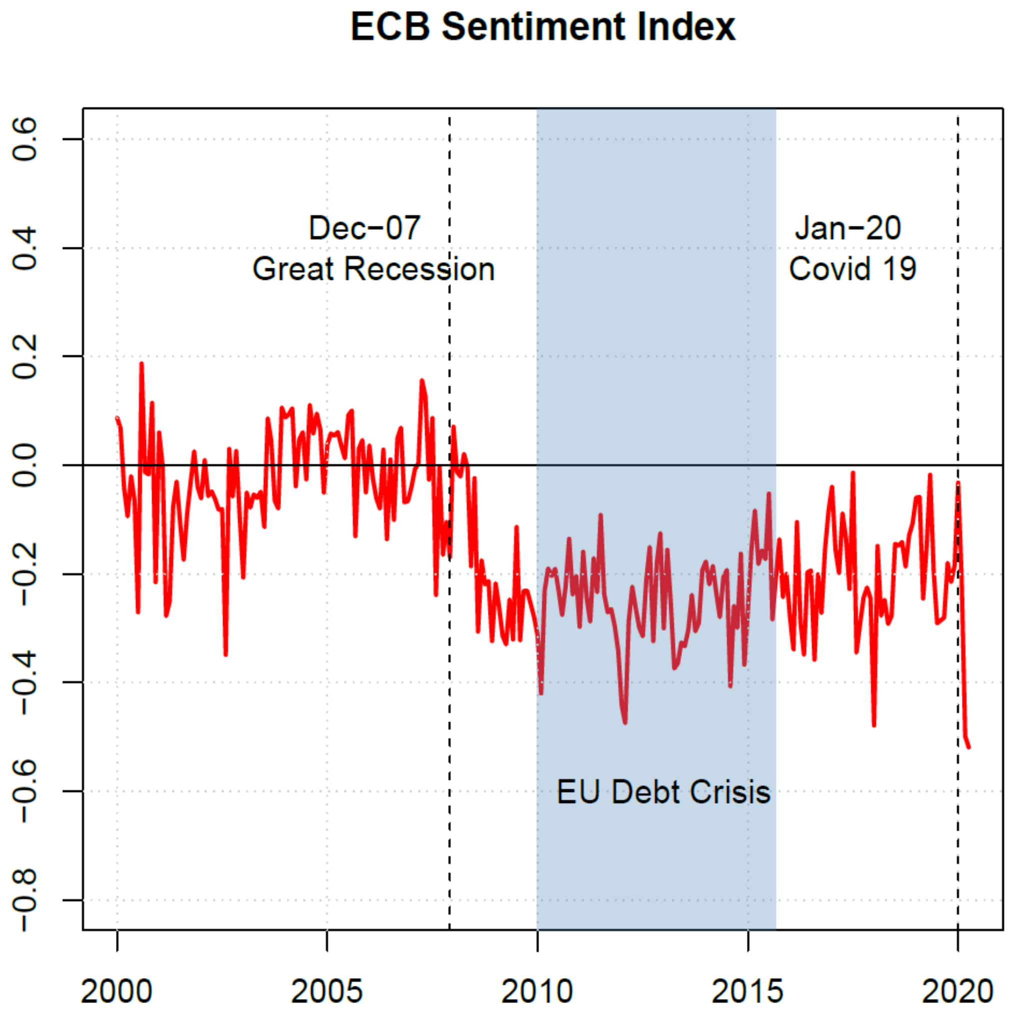
Central Bank Sentiment Index

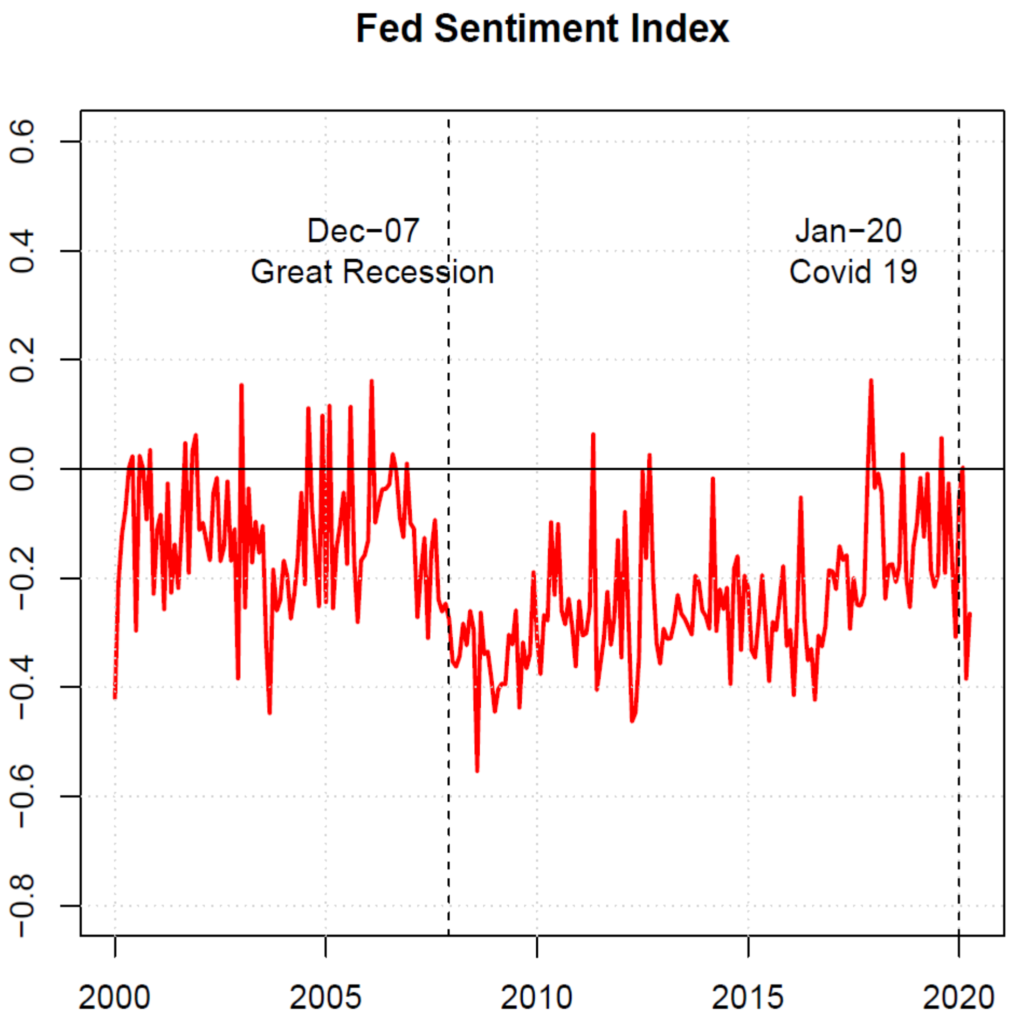
- Net score index (Birz and Lott, 2011);
- The denominator is the sum only of words with a (positive or negative) connotation that have been traced inside the text.
- **The score is comparable even among texts of different length.**
- **High scores indicate a positive view of the economic context** by the institution.

$$CBSI_t = \frac{(\#POS_t - \#NEG_t)}{(\#POS_t + \#NEG_t)}$$

Central Bank Sentiment Indexes

Monthly Sentiment Index – ECB and Fed





Sample: Jan 2000 – Apr 2020. Sources: European Central Bank, Federal Reserve, Federal Reserve Bank of St. Louis

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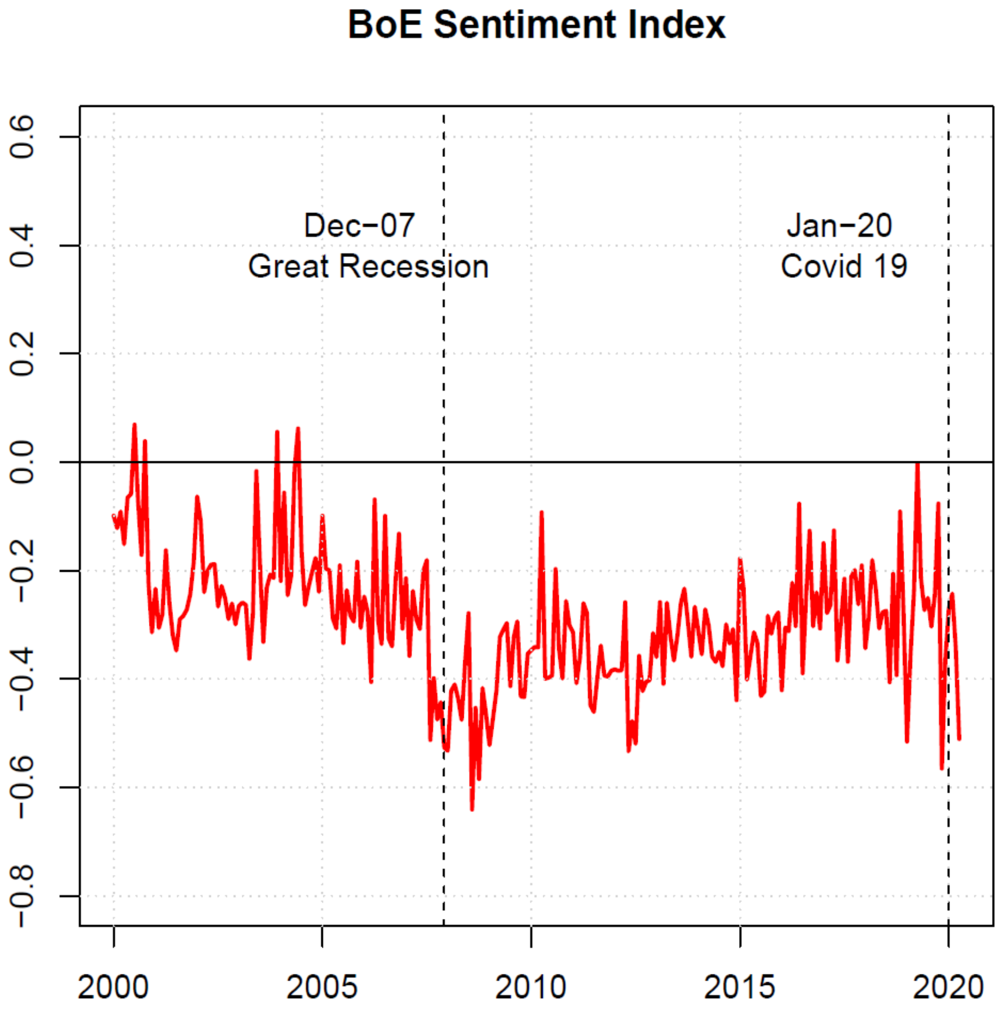
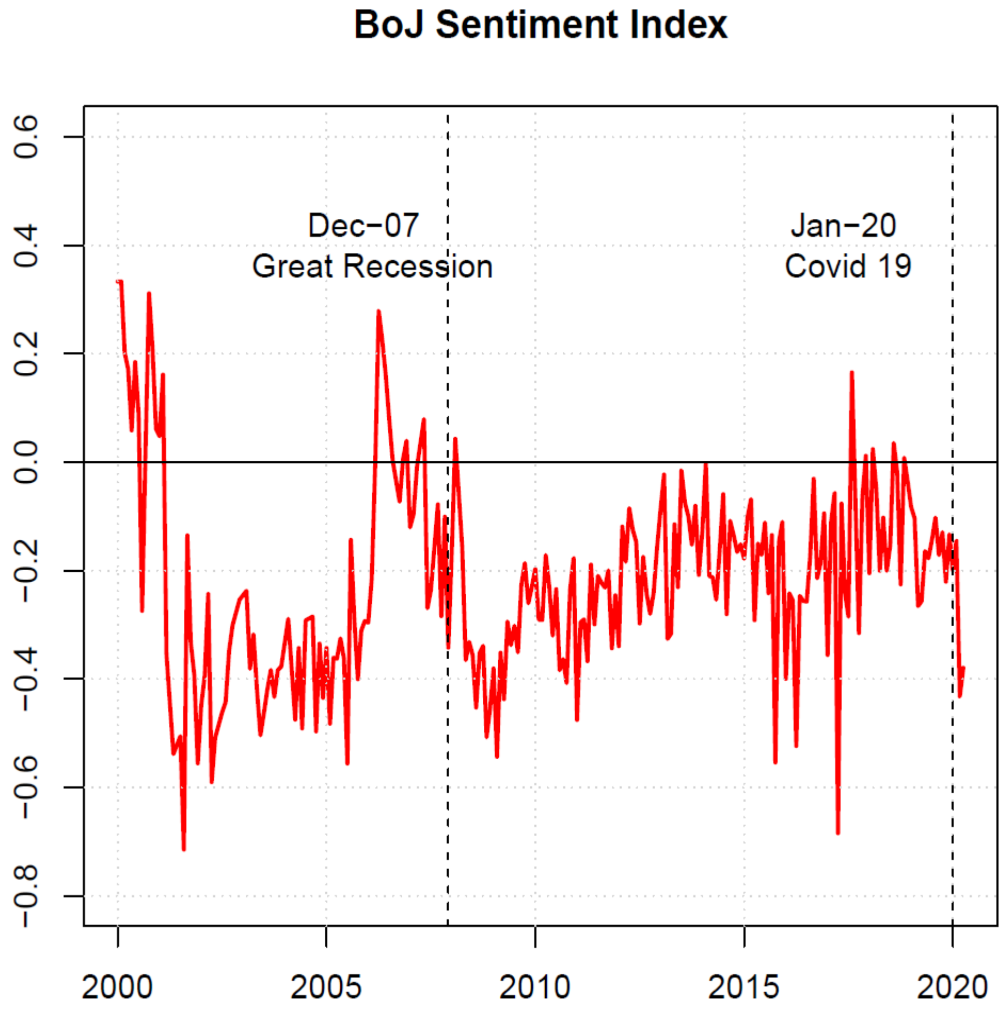
Central Bank Sentiment Indexes

Monthly Sentiment Index – BoE and BoJ





Sample: Jan 2000 – Apr 2020. Sources: Bank of England, Bank of Japan.

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Impact of CBSI on domestic financial variables

Methodology

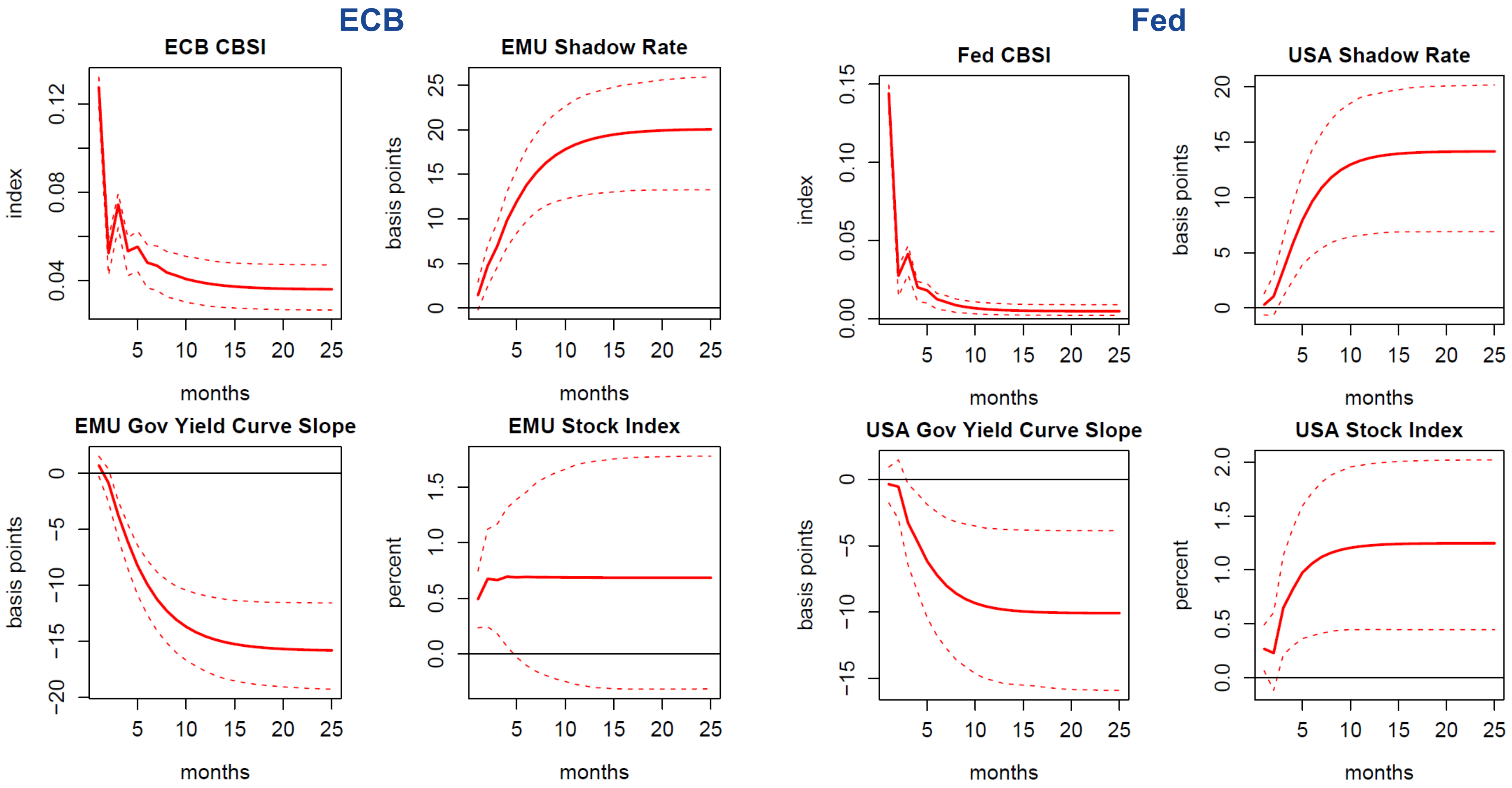
To investigate whether a change in CBSI has an impact on domestic financial variables:

1. We build a set of country-specific **Vector Error Correction Models** (VECMs) accounting for long-run cointegrating relationships among variables
   - We assume that central banks conduct their monetary policy following the Taylor Rule (Blinder et al., 2008) so they communicate their view of the prospects for inflation and output.
   - The variables in our analysis are: the **CBSI**, the **Shadow Rate** (Wu and Xia, 2016), the **log-level of the main domestic equity index** and the **slope of the government bond par yield curve** (10-year minus the 3-month).

2. We perform **Generalized Impulse Response Functions** (GIRF) (Pesaran and Shin, 1998):
   - with **Cholesky identification** the variables ordering matters (i.e. the shocks in the IRFs are sequential and not contemporaneous) (Diebold and Yilmaz, 2015);
   - we do not include **Sign-Restrictions constraints** in order to analyze the behavior of the variables in the system without imposing a priori assumptions;
   - The **GIRF** does not require orthogonalization of shocks and is invariant to the ordering of the variables in the model.

Impact of CBSI on domestic financial variables

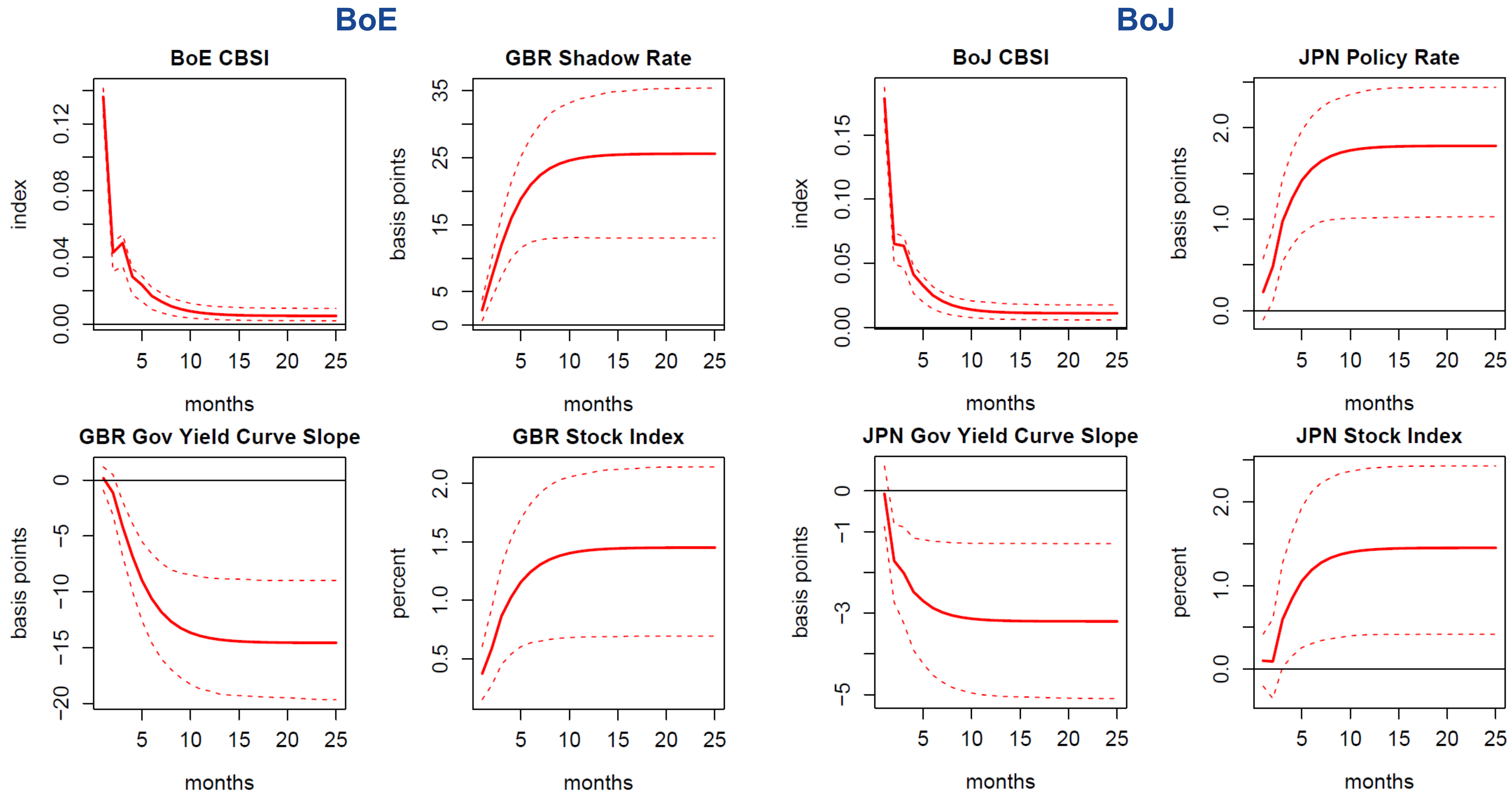
GIRF: Impact of Positive shock to CBSI (1/2)



Confidence intervals at 68%. Sample: Jan 2000 – Dec 2019. Financial variables source: Refinitiv. Stock Index: Euro Stoxx 50 for the Eurozone and S&P 500 for the USA.

Impact of CBSI on domestic financial variables

GIRF: Impact of Positive shock to CBSI (2/2)



Confidence intervals at 68%. Sample: Jan 2000 – Dec 2019. Financial variables source: Refinitiv. Stock index: FTSE100 for the UK and Nikkei 225 for Japan

Central bank connectedness

Methodology

To investigate whether and to what extent Central Banks influence each other through their communication, we propose a network approach.

In economic research, a network is a representation of interconnections between entities or countries, which can be derived through different econometric approaches. Among the others:

- Billio et al. (2012) concentrate on univariate models using pairwise Granger causality and obtain a directed adjacency matrix without a measure of spillover (the edges are 0 or 1);
- Diebold and Yilmaz (2015) employ the Generalized Forecast Error Variance Decomposition (GFEVD) to estimate a directed adjacency matrix but do not discriminate against negligible connections.

To overcome the drawbacks of these two methods, we propose a two-step approach:

1. We apply the **Network Estimation for Time Series** (NETS) methodology (Barigozzi and Brownlees, 2019) **to get a directed adjacency matrix identifying the relevant interconnections based on Multivariate Granger causality;**
2. Following the Diebold and Yilmaz (2015) approach, we assess the **spillover effect for each couple of vertexes** previously detected with NETS by means of the **GFEVD** (Pesaran and Shin, 1998).

Central bank connectedness

NETS

The **NETS** methodology (Barigozzi and Brownlees, 2019) performs network analysis on a large panel of time series assuming a zero-mean stationary $p-th$ order Sparse VAR:

$$Y_t = \sum_{q=1}^{Q} A_q Y_{t-q} + \varepsilon_t, \quad \varepsilon_t \sim iid(0, C^{-1})$$

- Both the inverse covariance matrix of the innovations C^{-1} and the autoregressive coefficient matrices A_q are assumed to be sparse;
- Such approach allows to jointly estimate and detect the non-zero entries of A_q e C^{-1} with a **new LASSO algorithm**;

The **Multivariate Granger causality** states that y_j Granger causes y_i if the first variable reduces the Mean Squared Forecast Error of the second one.

$$j\ GC\ i\ if\ \underbrace{E\left[\left(y_{i,t+h} - E\left[y_{i,t+h} | y_{1,t} \dots y_{N,t}\right]\right)^2\right]}_{MSFE\ with\ j} < \underbrace{E\left[\left(y_{i,t+h} - E\left[y_{i,t+h} | y_{1,t} \dots y_{N,t} \backslash y_{j,t}\right]\right)^2\right]}_{MSFE\ without\ j}$$

- As suggested by the authors, **the Granger causality structure of the model is encoded in the sparsity structure of the autoregressive matrices A_q**.
- Accordingly, it is straightforward to derive the adjacency matrix from LASSO estimation: **null elements in A_q matrix mean no Granger causality** (i.e. no connectedness between two entities).

Central bank connectedness

GFEVD

From the NETS stationary Sparse VAR, we can find its infinite **moving average (MA) representation**:

$$Y_t = \sum_{q=0}^{\infty} \Phi_q \varepsilon_{t-q} \ \ where\ \Phi_q = A_1 \Phi_{q-1} + \cdots + A_Q \Phi_{q-Q}$$

We then obtain the GFEVD, which allows to discern the contributions of each variable to the variance of the forecast error **H steps ahead**, in the following way:

$$\theta_{ij}(H=3) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Phi_h \Omega e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Phi_h \Omega \Phi_h' e_i\right)}$$

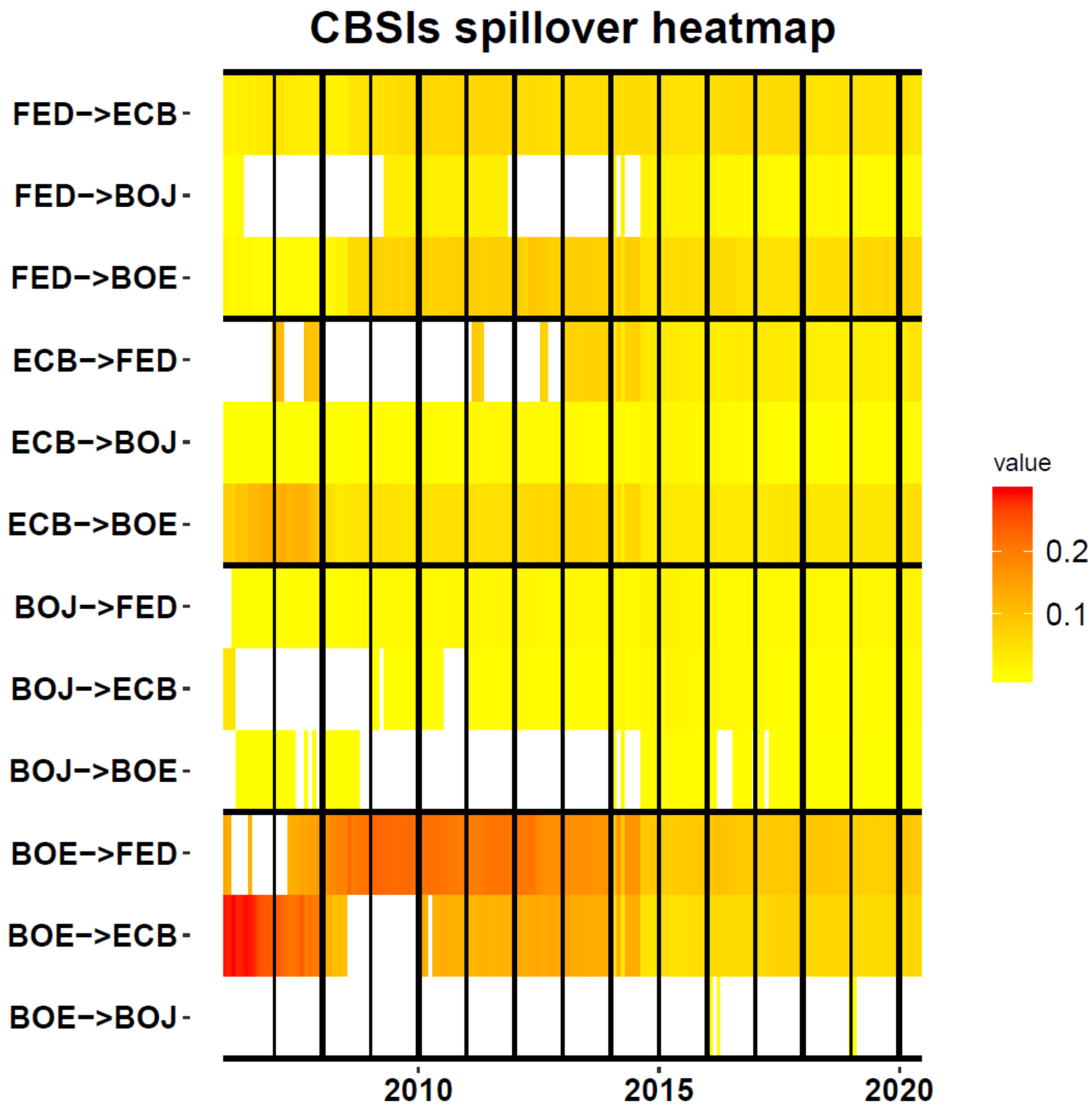
where e_i is the selecting vector (it is 1 in correspondence of the variable i^{th} and 0 otherwise).

- **The GFEVD is interpreted as a directional adjacency matrix**, being composed by pairwise directional interconnections;
- With the objective of assigning a “weight” (i.e. the spillover effect) to statistically relevant connections **we then multiplied the GFEVD with the NETS Granger causality adjacency matrix.**

Dynamic Communication Network[1]

Starting from January 2006 we iterate our two-step approach to assess **time-varying statistically significant spillover effects among central banks' communication:**

- **the main source of GFEVD of each CBSI is endogenous,** hence, central banks' sentiment is mainly affected by domestic economic conditions;
- nevertheless, **the spillover effects by other central banks' communication is sizable** (on average around 15 percent excluding the BoJ).



[1] A → B denotes the spillover effect from A to B conditional to multivariate Granger causality. Sample: Jan 2006 - Apr 2020

Conclusions

1. Using a large dataset that comprises speeches and press releases, **we compute a sentiment index for each central bank** (ECB, Fed, BoE and BoJ) with **text-analysis**:

   - **After the Financial Crisis all CBSIs shifted downward**, signaling a worsening in sentiment, with a **pronounced drop during the Covid-19 crisis.**

2. Through VECM and GIRF analysis for each country **we find that the way a central bank communicates has a significant impact on financial variables with the expected sign;**

3. We propose a **novel two-step approach to detect the relevant interconnections among CBSIs and to assess sentiment spillover effects** (NETS-GFEVD):

   - Although domestic economic conditions affect the CBSIs the most, **the sentiment indices generate time-varying cross-country spillovers**;

   - **In the aftermath of the financial crisis Fed's communication affected other central banks more than during the preceding and following years.**

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Confidentiality

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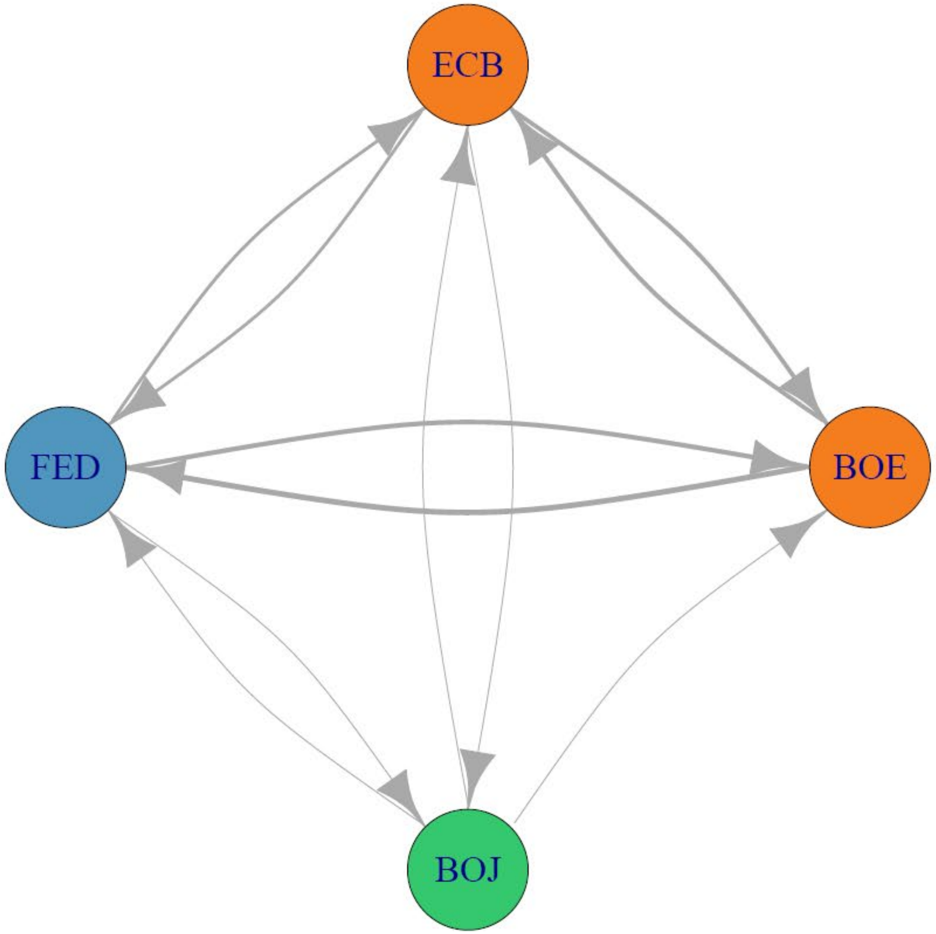
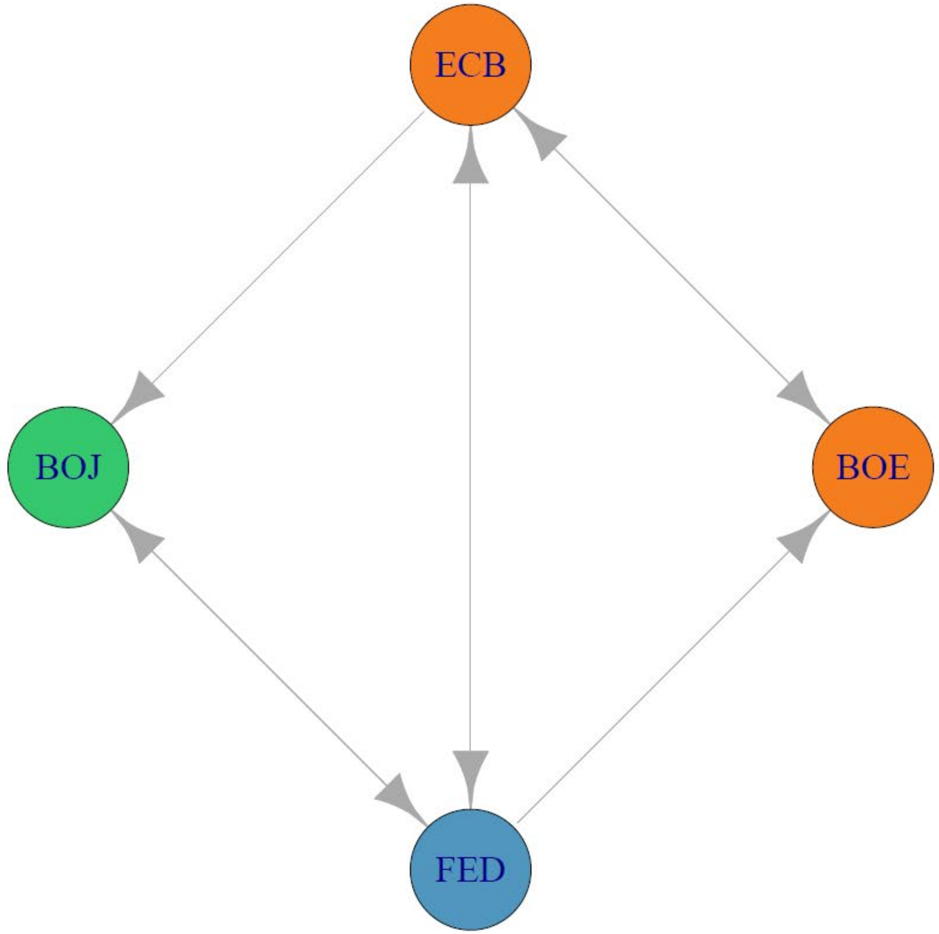
Full sample Communication Network vs Trade Network

A comparison

Two-Step Communication Network



Trade Network[1]



Sample: Jan 2000 - Apr 2020

[1]If country X is among the first five trade partners of country Y (on imports or exports side) an edge connects two vertexes and the arrow will point from X to Y. Source: IMF, 2019

Dataset Analysis with Tf-Idf

The 50 most «important» words for each Central Bank

ECB

Fed

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Dataset Analysis with Tf-Idf

The 50 most «important» words for each Central Bank

BoE

BoJ