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

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Introduction

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.

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.

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
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.

¹For 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

\[\text{Since we merged documents with the same date, we show the distribution of days with a speech. E.g. if there are two documents for the same day, the counting is one.}\]
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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
Central Bank Sentiment Indexes

Monthly Sentiment Index – BoE and BoJ

BoE Sentiment Index

Dec-07
Great Recession

Jan-20
Covid 19

BoJ Sentiment Index

Dec-07
Great Recession

Jan-20
Covid 19

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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)

Impact of CBSI on domestic financial variables

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

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.

$$j \text{ GC } i \text{ if } \frac{E \left( (y_{i,t+h} - E[y_{i,t+h}|y_{1,t} \ldots y_{N,t}])^2 \right)}{MSFE \text{ with } j} < \frac{E \left( (y_{i,t+h} - E[y_{i,t+h}|y_{1,t} \ldots y_{N,t} \setminus y_{j,t}])^2 \right)}{MSFE \text{ without } j}$$

- 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:

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

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:

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

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.
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).
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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.
Back up slides
Full sample Communication Network vs Trade Network

A comparison

Two-Step Communication Network

Trade Network

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

market bank area polici euro increase growth stabil rate

Fed

market polici risk rate bank year import firm recent credit

prometeia
Dataset Analysis with Tf-Idf

The 50 most «important» words for each Central Bank

BoE

rate, policy, growth, inflation, market, finance, economy, bank, risk, price, interest, time, level, rise, demand, firm, will, like, new, recent, around, develop, target, stabilize, fund, measure, output, growth, system, lead, valid, work, activity, continu, market, bank, firm, level, decline, current, recent, new, system, measure, fund, target, stabilize

BoJ


prometeia