Measuring central banks' sentiment and its spillover effects with a network approach*

Preliminary Draft

Maria Paola Priola† Piero Lorenzini‡ Giacomo Tizzanini§ Lea Zicchino¶

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Abstract

Since the financial crisis, a new tool has been more extensively used by Central Banks around the world, namely communication. The importance of the guidance coming from Central Banks increased together with the introduction of the so-called unconventional monetary policy measures, i.e. all the measures other than changes in the short-term interest rate. To analyze the effectiveness of Central Banks communication we do several things. First, we construct a Central Banks' Sentiment Index (CBSI) for the BoE, the BoJ, the ECB and the Fed by applying text analysis to a large dataset of speeches and releases. We then investigate spillovers generated by sentiment index on domestic financial variables with Generalized Impulse Response Analysis. Finally, we propose a network-based two-step approach to analyze the time-varying spillovers among central banks' communication, identifying statistically significant dependencies and assessing their spillover effects. We find that after the Great Recession all CBSIs considerably shifted downward, i.e. sentiment conveyed by CBs became more negative. Second, by means of word clouds, we observe that central banks' communication shares common terms. Third, our CBSIs are positively related to monetary policy decisions and the stock market and negatively to the yield curve slope. Finally, sentiment indices affect each other and these effects are time-varying, with an increasing influence of the Fed on other central banks after the Great Recession.

Keywords: central banks, communication, monetary policy, text analysis, network, spillover effects.

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*Any errors are of the authors. The views expressed in this paper are those of the authors and do not necessarily represent the opinions of Prometeia S.p.A.

†Prometeia. E-mail: mariapaola.priola@prometeia.com

‡Prometeia. E-mail: piero.lorenzini@prometeia.com

§Prometeia. E-mail: giacomo.tizzanini@prometeia.com, corresponding author.

¶Prometeia. E-mail: lea.zicchino@prometeia.com

1 Introduction

Over the last years the academic literature has widely acknowledged that central banks' communication has an impact on the economy. This fact might be due to both the increase in transparency and in the amount of information released by central banks (Dincer and Eichengreen, 2014; Apel and Grimaldi, 2012; Acosta, 2015).

Moreover, it seems that not just the content but also the economic sentiment embedded in central banks' communication is of outmost importance for both market participants and policymakers. However, in contrast with other quantitative economic indicators that are easily readable and accessible, communication sentiment is not directly quantifiable. Accordingly, researchers started to use text analysis techniques to translate the qualitative information contained in central banks' communication in a quantitative indicator (Loughran and McDonald, 2011; Apel and Grimaldi, 2012; Correa et al., 2017; Armelius et al., 2020; Picault and Renault, 2017). A newly created variable that proxies the sentiment in central banks' communication can then be used to quantify its effects on macroeconomic and financial variables and to shed light on interconnections among central banks through sentiment (Armelius et al., 2020; Picault and Renault, 2017). Furthermore, such an indicator might be employed as a more efficient alternative to surveys-based indices on economic sentiment (Shapiro et al., 2020).

Researchers have traced central banks' communication influence over different variables: while Rosa (2011) and Kurov (2012) analyze its effects on stock prices; Fratzscher (2008), Égert and Kočenda (2014) study how exchange rates react to change in monetary policy communication. Moreover, Hansen and McMahon (2016) and Hansen et al. (2019) examine how interest rates and macroeconomic real variables respond to central banks' communication. Moving the attention to market volatility, Ehrmann and Talmi (2020) show that changes in the ways central banks communicate (i.e. "substantial textual changes after a sequence of very similar statement") might lead to higher market volatility. On the same note, Jubinski and Tomljanovich (2017) find that conditional volatility increases after Federal Reserve's announcements.

Only recently researchers' interest shifted from the impact of (un)conventional monetary policy measures (Eichengreen and Gupta, 2015; Fratzscher et al., 2016) to the presence of potential spillover effects due to central banks' sentiment. Picault and Renault (2017) test the impact of their ECB economic sentiment indicator on monetary policy decisions taken by the governing council, both in terms of interest rates and unconventional measures (e.g. Quantitative Easing); they found that their measure conveys relevant information to explain future policy decisions. Similarly, Apel and Grimaldi (2012) observe that their indicator for the Riksbank could efficiently be used to forecast policy rate decisions. Other researchers concentrated on different effects: Bennani (2019) develops an indicator for the People Bank of China from speeches released by the institution and finds that positive changes in the indicator positively affects stock prices. Correa et al. (2020) build a *Financial Stability Index* for 35 different central banks and discovers that it affects variables related to credit, asset prices, and systemic risk. On a similar note, Armelius et al. (2020) investigate the impact of a sentiment index constructed for 23 central banks on a set of macroeconomic variables through Sign Restriction VARs models with Impulse Response analysis and explore Central Banks' interactions through communication, using a static model based on pairwise Granger causality, as described by Billio et al. (2012). First, they find that sentiment shocks generate cross-country spillovers on policy rates, sentiment and macroeconomic variables, with the Federal Reserve resulting as the leading spillover generator among central banks. Second, geographic distance and shared language have a determinant role in explaining co-movements in central bank sentiment.

We contribute to the empirical literature along several dimensions. Following Loughran and McDonald (2011), we construct our own Central Bank Sentiment Indexes (CBSIs), applying text analysis to a novel dataset that comprises releases and speeches published by the Federal Reserve (Fed), the European Central Bank (ECB), the Bank of England (BoE) and the Bank of Japan (BoJ) between 2000 and 2020. In addition, we create word clouds for the fifty most important words for each central bank using the Terms Frequency-Inverse Document Frequency function (Tf-Idf) (Baeza-Yates et al., 1999). Then, we perform Generalized Impulse Response Functions (GIRF) analysis to shed light on the effects of central banks' communication on financial variables. Finally, we examine the time-varying interconnections and spillover effects among central banks in terms of sentiment. For this latter analysis, we propose a two-step procedure: (i) we apply the Network Estimation for Time Series (NETS) estimator (Barigozzi and Brownlees, 2019) to identify statistically significant dependencies through multivariate Granger causality; (ii) we assess their spillover effects from a Generalized Forecast Error Variance Decomposition (GFEVD) following the framework of Diebold and Yilmaz (2015). To the best of our knowledge, such an approach has never been applied before to Central Banks' communication.

Our main findings are the following. First, after the Great Recession and the Financial Crisis all CBSIs considerably shifted downward, signaling a worsening in sentiment, probably due to a permanent change in communication by central banks (a business cycle with weak growth and/or sluggish inflation has induced a more cautious communication with the public), with a pronounced drop during the Covid-19 crisis. Second, from the word clouds we observe that many terms are shared by all central banks, (i.e. "policies", "inflation", "risk" and "rate") with some differences in the importance of the words for each institution.[1] Third, a positive shock to Central Bank communication seems to have a positive and significant impact on the shadow rate and the stock market index, but negative on the yield curve slope (consistently with findings obtained by Armelius et al., 2020). In particular, for the USA, the UK and Japan the aforementioned effects become statistically significant within three months. Instead, for the Eurozone we observe mixed responses. Fourth, Central Banks' sentiment indexes are connected (with the sole exception of BoE vs BoJ) and the most relevant spillovers are between the Fed and the BoE. Moreover, our two-step network partly differs from that derived from trade flows, since a Central Bank's prominence in the network does not coincide with its relative economic importance. Fifth, the most original contribution of our paper is the evaluation of time-varying connectedness and spillover effects of sentiment indices. We find that the Fed influences the other Central Banks for the whole period of analysis, with an increasing magnitude after the Great Recession, proving its "leading role". After the European debt crisis, the ECB increased its relevance, whereas the BoE gradually reduced it. Finally, the BoJ seems to have a lower impact on other central banks' communication.

This paper is organized as follows. Section 2 reviews the literature on text analysis applied to economic research with a focus on central banks' communication. In Section 3 we describe how we constructed the CBSIs. In Section 4, after a brief introduction on our econometric approach, we present the results of our analyses. Section 5 introduces considerations for future research and provides some concluding remarks.

2 Literature Review

Text sentiment analysis is a branch of Natural Language Processing (NLP) and is now employed for many purposes, such as social media analysis, digital trading, customer experience management, economic and financial research. The related literature in the field of economics is rapidly growing; the technique provides various ways to quantify a sentiment indicator for different types of economic texts (i.e. articles, speeches, notes, minutes etc.). Apart from Machine Learning (ML) techniques (Liu et al., 2010), which are still at an embryonal stage when applied to economics text analysis (Shapiro et al., 2020), most researchers that employ text sentiment analysis to economic issues utilize the *lexical* approach.

This method consists in automatically matching a set of words with a pre-given connotation, that is a *dictionary* (or *lexicon*), to words in the text of interest. Word connotation could be proxied by a simple indicator variable (e.g. Positive=1, Negative=-1) or by a score ranging between two particular values (e.g. from -1 to 1). However, as noted by Loughran and McDonald (2011), most dictionaries are not specifically built for economic texts, hence some words inside them could have an opposite connotation if considering a financial or an economic context. Therefore, they built their own dictionary

[1] A word is important if it is contained in a document (*term frequency*) but is less frequent among all documents (*inverse document frequency*). For an exhaustive definition, see Section 3.4.

precisely designed for the domain of finance and economics (LM dictionary). This particular lexicon has been vastly used in the literature: among the others, Shapiro and Wilson (2019) applied it to minutes of the Federal Open Market Committee's meetings; Armelius et al. (2020) used it for Central Bankers' speeches. Correa et al. (2017) adopted a similar approach, designing their own "Financial Stability" (FS) dictionary. Likewise, Henry and Leone (2016) constructed a finance-specific lexicon for their analyses. Another approach that researchers might choose is to build a dictionary that not only is domain-specific but also institution-specific; that is, a lexicon focused on documents released by a particular organization. The rationale behind such an approach is that every economic/financial entity has its own way of communicating; hence, words could have a different connotation for each institution. Examples of this method are traceable in the dictionaries created by Picault and Renault (2017) and Apel and Grimaldi (2012); respectively tailored for the European Central Bank (ECB) and the Swedish Central Bank (Riksbank). Nevertheless, even though this technique could entail positive results, it is very time consuming if the analysis covers various institutions.

After having determined the frequency of words with their particular connotation, the following step in the *lexical* approach is to build an indicator. In the literature there are different methods to construct an indicator. Several researchers use variants of the following formula (Armelius et al., 2020), named *Positive Score Index*:[2]

$$Positive\ Score\ Index_t = 1 + \frac{(\#Positive_t - \#Negative_t)}{\#Total_t}, \tag{1}$$

where the difference between *positive* and *negative* words is divided by the *total* of the words in the text. This score allows to account for the level of dispersion of words with connotation inside the document. However, if the texts analyzed differ greatly in terms of length, distortions in the indicator might arise. Hence, other approaches have been developed to overcome this issue. For instance, Apel and Grimaldi (2012)[3] use a method of computation proposed by Birz and Lott Jr (2011), named *Net Score Index*:

$$Net\ Score\ Index_t = \frac{(\#Positive_t - \#Negative_t)}{(\#Positive_t + \#Negative_t)}. \tag{2}$$

Being the denominator the sum of only words with connotation that have been traced inside the text, the score is comparable even among texts with different length without creating distortions in the indicator.

The range of the Net Score Index is between -1 and 1, whereas the Positive Score Index can vary between 0 and 2. Both indexes should be interpreted in the same way: high scores indicate a positive view of the economic context by the institution, whereas low levels denote a negative outlook.

The final step that researchers generally adopt is to aggregate in monthly or quarterly averages the indexes related to single documents and to perform econometric analyses with these newly generated time series (Picault and Renault, 2017; Shapiro et al., 2020; Correa et al., 2020; Armelius et al., 2020).

As previously noted, the objective of deriving a sentiment indicator for Central Banks' communication is to determine its possible impact on monetary policy decisions and macroeconomic and financial variables (Picault and Renault, 2017; Apel and Grimaldi, 2012) but also to verify to what extent central banks influence each other (Armelius et al., 2020).

3 Prometeia Sentiment Index

We build our Central Banks' Sentiment Indexes (CBSIs) following the steps in the *lexical* approach explained in the previous section using the *Net Score Index* computational approach. We construct our

[2] The method introduced by Armelius et al. (2020) is based upon an elaboration of computational methods that can be traced also in the work by Correa et al. (2020) and Loughran and McDonald (2011).

[3] The authors do not utilize the *positive* and *negative* connotation but instead they refer to *hawkish* and *dovish*.

indicator for four Central Banks, namely the Fed, the ECB, the BoE and the BoJ. Our choice has three motivations. Firstly, these institutions are the central banks of economies accounting for nearly 50% of global Gross Domestic Product (IMF, World Economic Outlook, April 2020); hence, it is very likely that their communication is highly influential. Secondly, they are ranked among the most transparent central banks (Dincer and Eichengreen, 2014); therefore, their communication is expected to convey a lot of valuable information. Finally, strictly related to the previous point, they release the highest amount of communication. This feature allows for the construction of more robust monthly indicators.

This section is organized as follows. First, we provide an overview of the types of texts used to build the CBSIs and describe our method for processing the data. Then, we present the results of our CBSIs; finally, we create word clouds for terms with the highest weighted frequency in the dataset by way of Information Retrieval techniques.

3.1 Data

In the literature on text analysis applied to central bank communication, some researchers concentrated mostly on speeches (Bennani, 2019). Instead, Correa et al. (2020) build an indicator based upon financial stability reports published by central banks. Indeed, in the literature it is acknowledged that releases to the public as part of central bank communication are important. For example, Picault and Renault (2017) considered ECB releases for their research and Armelius et al. (2019) recognized that central banks' releases might convey more relevant information than speeches. Therefore, we chose to include both types of texts in the dataset and this allowed us to substantially increase it.

Our dataset comprises a collection of speeches and releases from the institutional website of each central bank,[4] with the exception of the FOMC transcripts, which were downloaded from the official website of the Federal Reserve Bank of St. Louis.[5] Generally, speeches can vary in their format, depending on the event at which the speech is delivered. Instead releases are shorter and standardized, as they are the summary of monetary policy decisions or press releases with a focus on monetary policy.

However, two issues need to be addressed. First, more speeches and releases are published on the same day, leading to a potential distortion for the index computation. To overcome this issue, we decide to merge documents with the same date so to have a single value indicator for each publication date in the dataset. Second, due to the presence of documents with different length, we opt to use the *Net Score Index*,[6] which permits to standardize the index.

Overall, our dataset includes 5801 documents distributed as in Table 1 and it spans from January 2000 to April 2020.

Table 1: Composition of our dataset

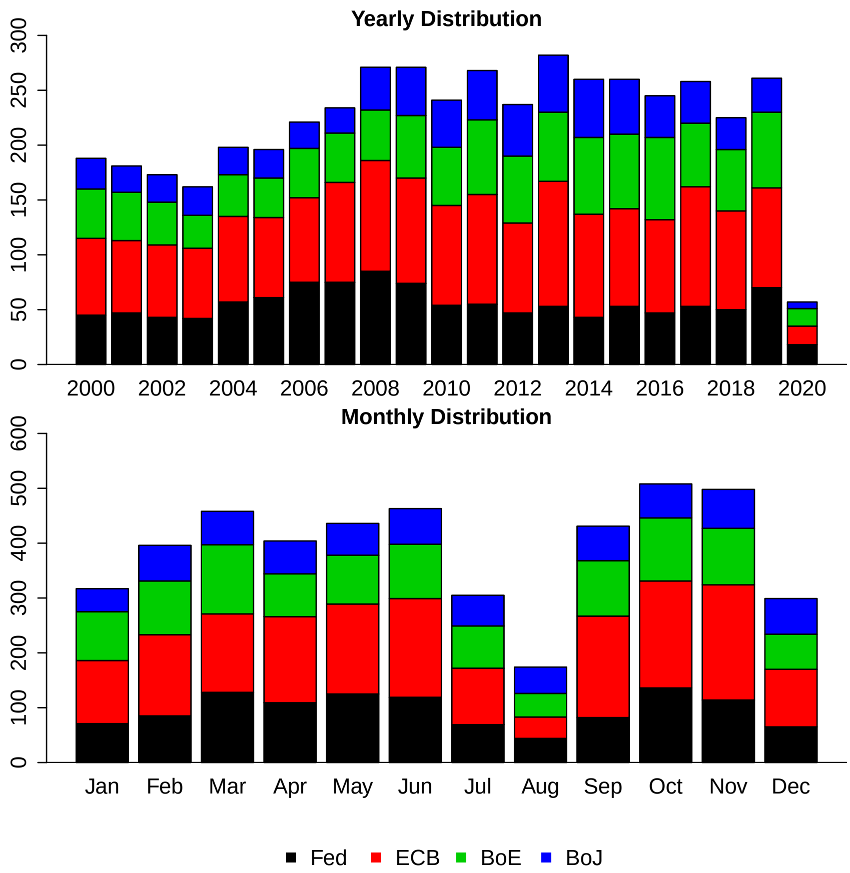
	Fed	**ECB**	**BoE**	**BoJ**
Total	1456	2238	1251	847
Yearly Average	72	111	62	42

In addition, from Figure 1 the monthly and yearly distribution of our dataset can be inferred.

Ultimately, it is worth noting that the amount of documents published by Central Banks has increased steadily from the first half of the 2000s, later stabilizing in the 2010s. This finding is in line with the increase in Central Banks' transparency noted by Dincer and Eichengreen (2014). As far as the ECB, the BoJ and the BoE are concerned, we notice a substantial increase in publications between 2006 and 2010, signaling that the financial crisis and the Great Recession had an impact on central banks' transparency. On a different note, the highest increase for the Fed is observable during the last

[4] Including summary of Monetary Policy decisions and Press Releases related to monetary policy.
[5] www.fred.stlouisfed.org
[6] Section 2 contains a detailed explanation of the Net Score Index.

Figure 1: Yearly and monthly distribution of speeches and releases for each central bank



years of Greenspan's chairmanship: indeed, while in 2003 the total number of publications was only 64, in 2005 it was 108. Finally, all banks in our sample have increased the number of publications from the first decade of the century with the exception of the Fed, which has decreased its publications.

3.2 Pre-processing

After having prepared the dataset with *raw* data in .txt format, we apply a set of text mining techniques following the literature in the field of NLP (Silge and Robinson, 2017). Such transformations are necessary to process the documents. In detail, the raw data are converted in a *text-corpus*[7] following a methodology detailed by Hornik and Grün (2011). We *clean* the text by converting it to lowercase and then removing numbers, extra spaces, punctuation and regular expressions. A stemming algorithm is also applied to eliminate common suffixes and prefixes. Finally, we tokenize the text, that is, the text is categorized in blocks readable by the software.[8] After this pre-processing phase, we achieve a *document-term matrix*,[9] which is used to calculate the indicator.

3.3 Central Bank Sentiment Index

In order to obtain the CBSIs we choose the LM dictionary, matching words with positive/negative connotation for all the documents of each central bank. This choice of lexicon is driven by the broad

[7]A text-corpus is a set of structured and standardized texts on which is possible to apply statistical and computational analysis.

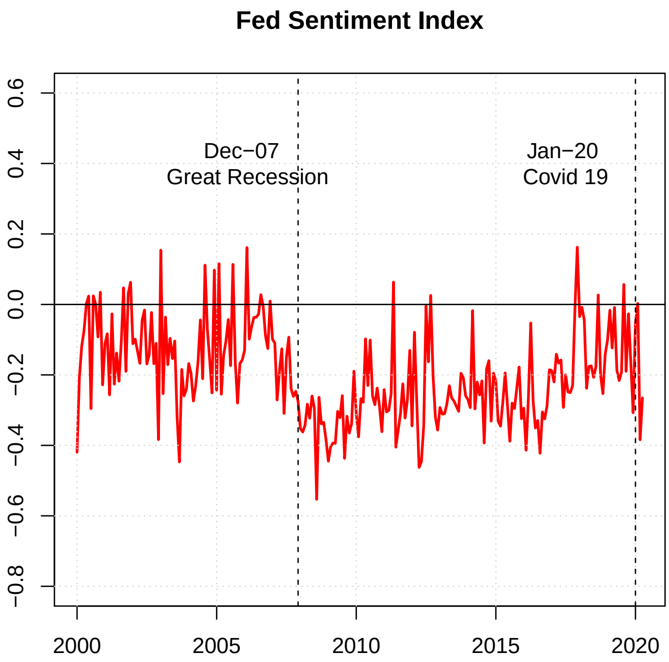
[8]For this research we utilized the R software.

[9]A *document-term matrix* is a numerical matrix that contains the frequency of terms in a set of texts. In particular: "the rows in this matrix correspond to the documents and the columns to the terms. The entry $m_{i,j}$ indicates how often the *j-th* term occurred in the *i-th* document".

consensus in the literature on the validity of this dictionary when applied to finance text analysis (Shapiro and Wilson, 2019; Armelius et al., 2020). Therefore, as previously noted, we compute the *Net Score Index* for each day in which a speech or a release is published by central banks. Finally, we calculate monthly averages of the indicator.

In Figures 2-5 we show the CBSIs time series and highlight both global and country-specific events, such as the Great Recession and the beginning of the Covid-19 crisis (dotted lines) and the European Debt Crisis (shaded area). In Table 2 we provide some summary statistics of our monthly CBSIs over the sample period (2000-2020) and for three different subsamples, namely the years before the Great Recession, the period of the crisis (2008-2010) and the subsequent decade (2011-2020).

Figure 2: Fed CBSI



For all banks, the indicators shifted downward after 2007. It is possible that there is a structural break in the time-series caused by the Great Recession and the relative Financial Crisis; indeed, even for the following period (2011-2019) the CBSIs' averages are considerably lower than for the period 2000-2007. Only the average for the BoJ's index is higher after the crisis.[10] This finding could signal a permanent change in communication by central banks: the financial crisis might have induced them to become more cautious when communicating with the public. Releases and speeches are in effect less positive in their content. Moreover, it is important to consider that the recovery from the Great Recession was not synchronized among economic areas, with the Eurozone struggling more than the other countries to return to pre-crisis growth levels. This fact might have contributed to the higher negative impact on ECB sentiment vis-à-vis other CBSIs. Despite a lower indicator on average than at the beginning of the period of analysis, the CBSIs improved after the crisis. In particular, the Federal Reserve reached its lowest point in sentiment in 2008 (-0.55), but then sentiment steadily increased in the 2010s. In addition, for the BoE and the BoJ the CBSIs improved during the period of economic recovery, although Brexit affected the BoE. This is not the case for the ECB. Indeed, ECB's

[10]However, the higher standard deviation for the period 2000-2007 (0.24) than for the period 2011-2020 (0.13) means that the index is particularly erratic before the Great Recession. This might be due to the lower availability of data for the BoJ at the beginning of the 2000s, hence the indicator might be distorted for the period before the Great Recession.

Figure 3: ECB CBSI

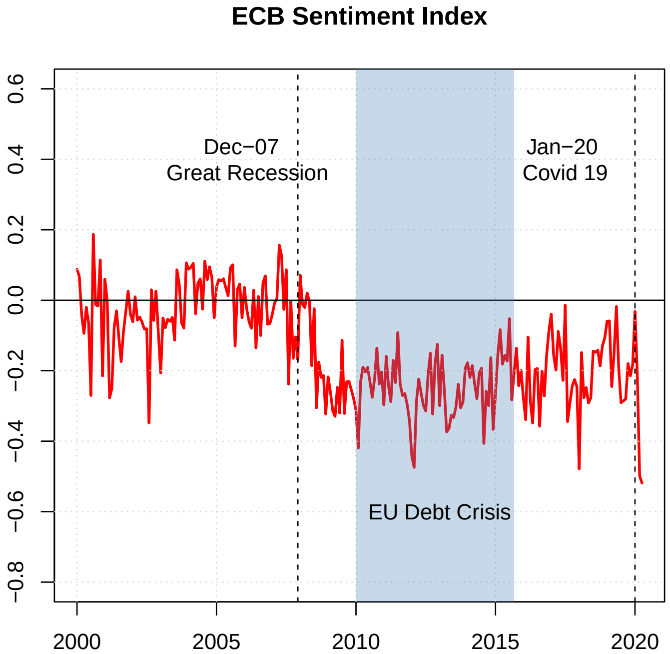


Figure 4: BoE CBSI

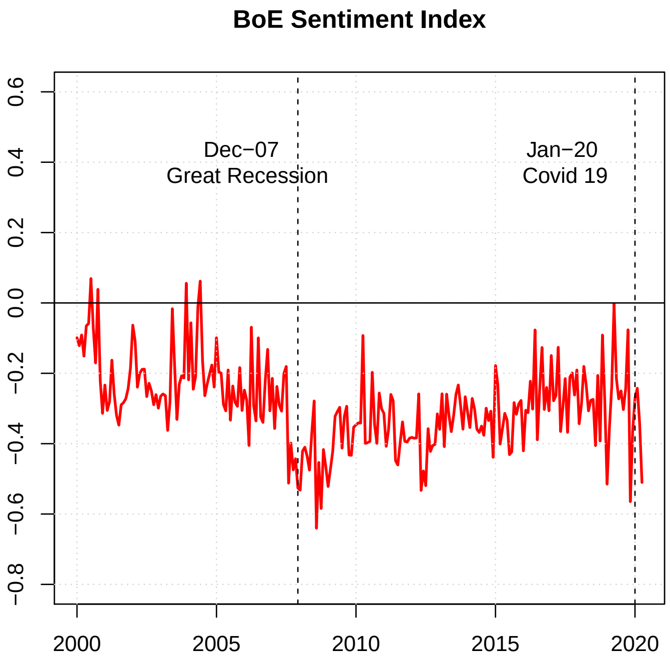
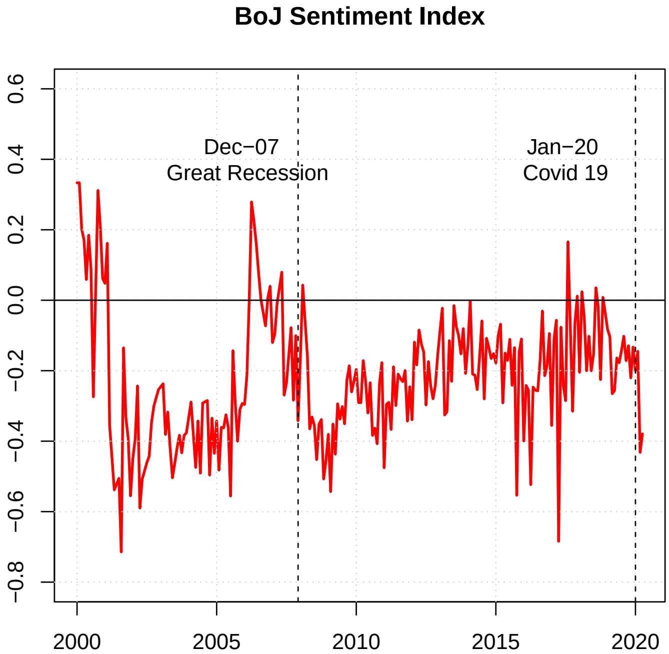


Figure 5: BoJ CBSI



average CBSI over the period 2011-2019 is even lower than the average for the period 2008-2010. This might be due to the European debt crisis that characterized the years from 2010 to 2015. Finally, it is remarkable the dramatic drop in sentiment for all Central Banks in 2020 following the worldwide spread of the Covid-19 crisis. In particular, ECB's sentiment reached its historical minimum in April 2020 (-0.52).

3.4 Dataset Analysis with Tf-Idf Methodology

To analyze the topic content of our dataset, we compute the *Terms Frequency-Inverse Document Frequency* (Tf-Idf) function (Baeza-Yates et al., 1999) and we provide a visual representation using word clouds, which contain the fifty most important words from the entire collection of documents for each bank.

The Tf-Idf is a function that weighs the importance of a term within to the whole dataset (Leskovec et al., 2014). The function is expressed as:

$$(tf - idf)_{i,j} = tf_{i,j} * idf_i \tag{3}$$

with

$$tf_{i,j} = \frac{n_{i,j}}{|d_j|}; \quad idf_i = log\left(\frac{|D|}{|d : i \in d|}\right) \tag{4}$$

where $tf_{i,j}$ stands for Term Frequency of word i in the document j; $n_{i,j}$ is the number of occurrences of word i in the document j, while d_j is the length of document j as the sum of its terms. In addition, idf_i stands for Inverse Document Frequency of word i in the collection of documents D; and $|D|$ is the sum of the documents in the sample. The denominator measures the number of documents in which i is present.

This function grows proportionally with the number of the occurrences of the word in the document and it decreases when there is an increase in the absolute frequency of the word in the dataset. The idea behind this approach is to give more importance to terms that are present in the document but that are less frequent among all documents.[11] The resulting rank of words is therefore more significant than the absolute frequency approach. This measure gives low weight to terms that have low frequency within a document, as well as to those occurring in many (Hornik and Grün, 2011). The fifty terms with the highest weighted frequency in each central bank's dataset are shown in Figure 6.[12]

Figure 6: Central Banks Word Clouds

(a) Fed

(b) ECB

(c) BoE

(d) BoJ

A larger font indicates that a term is used with a higher frequency in its respective text corpus. Green, red and black indicate term frequency clusters (high, average and low frequency).

In the word clouds, the rank of words is represented both by the color and by the size of the words. It can be seen that many terms are common to all banks: notably, "policies", "inflation", "risk" and "rate", possibly indicating that central banks use a similar vocabulary. Nevertheless, there are some peculiarities to notice: while "rate" is among the first words extracted for the BoJ, the BoE and the Fed, this is not the case for the ECB. Furthermore, for the BoE, both the words "growth" and "inflation" are more frequent than for the other banks; hence the BoE seems more concerned both

[11] It is important to note that we apply Tf-Idf only for dataset analysis. To compute the indicator, we use the absolute frequency.

[12] The stemming algorithm transforms "y" suffixes in "i". As an example, "monetary" becomes "monetari".

about growth and inflation, even though its mandate does not refer explicitly to economic growth, but only to price and financial stability.

4 Empirical Analysis

This section introduces the model theoretical framework and presents the results of our analysis. In particular, we apply Generalized Impulse Response Functions (GIRF) to investigate whether a change in central bank communication - that is, the sentiment indicator - affects domestic monetary policy, equity markets and the government bond yield curve. Then, by applying a two-step procedure: (i) we detect the relevant interconnections among central bank sentiment indices by means of NETS, the novel LASSO shrinkage estimator defined by Barigozzi and Brownlees (2019); (ii) we assess sentiment spillover effects from a Generalized Forecast Error Variance Decomposition (GFEVD) following the approach by Diebold and Yilmaz (2015).

4.1 Generalized Impulse Response Analyses

We interpret our sentiment index based on the assumption that central banks conduct their monetary policy in accordance with the Taylor Rule (Blinder et al., 2008). Therefore, similarly to Armelius et al. (2020), we build a set of country specific Vector Error Correction Models (VECMs) accounting for long-run cointegrating relationships among variables to verify if bank communication (CBSI) generates domestic spillovers.

As previously mentioned, our focus is to determine the impact of a change in our CBSIs on financial variables. Therefore, the variables we include in our analysis for each VECM are the following: (i) the CBSI;[13] (ii) the shadow rate,[14] which summarizes monetary policy actions when the Zero Lower Bound is reached (Wu and Xia, 2016); (iii) the log-levels of the main domestic equity index;[15] (iv) the slope of the par yield government bond curve[16] (see Table 3). Following the Johansen cointegration test, we accept the null hypothesis of at least one cointegrating relationship in each country-specific model. The sample period is from January 2000 to December 2019 and all variables are in levels.

To assess the spillover effects, we perform GIRFs where the impulse is a shock to each CBSI. Differently from Armelius et al. (2020), we do not include Sign-Restrictions constraints in order to analyze the behavior of the variables in the system without imposing a priori assumptions. As noted by Diebold and Yilmaz (2015), in a VAR framework the Cholesky identification implies that the ordering of the variables becomes important when considering Impulse Response Functions (IRFs) (i.e. the shocks in the IRFs are sequential and not contemporaneous). Therefore, many researchers apply the methodology introduced by Pesaran and Shin (1998), namely Generalized Impulse Response Analysis (GIRFs). As stated by the authors, one of the advantages of such an approach is that it does not require orthogonalization of shocks and is invariant to the ordering of the variables in the VAR. Indeed, it is possible to account for shocks considering all patterns of correlations among variables.

In Figures 7-10 we show the spillover effects of central bank communication from GIRFs for each country with confidence intervals at 68%. A positive shock to sentiment seems to have positive and significant impact on the shadow rate and the stock market index, but a negative one on the slope of the yield curve. The latter response may seem unusual, but as Lane (2019) noticed: more recent papers account for the fact that monetary policy decisions have typically been accompanied by explicit (or at least perceived) central bank communication on the future course of policy rates. Considering an improvement of CBSI as a *"rate surprises"*, a standard rate hike affects the short-term yield more (the impact peters out monotonically across the curve), therefore flattening the curve. In particular, for the USA, the UK and Japan the aforementioned effects become statistically significant within

[13] In each model we rearrange the CBSI as an unbounded variable with the following steps: (i) $CSBI^* = (CSBI+1)/2 \in [0,1]$; (ii) by means of inverse normal distribution we get $CSBI^{IG} = IG(CSBI^*) \in [-\infty, +\infty]$.

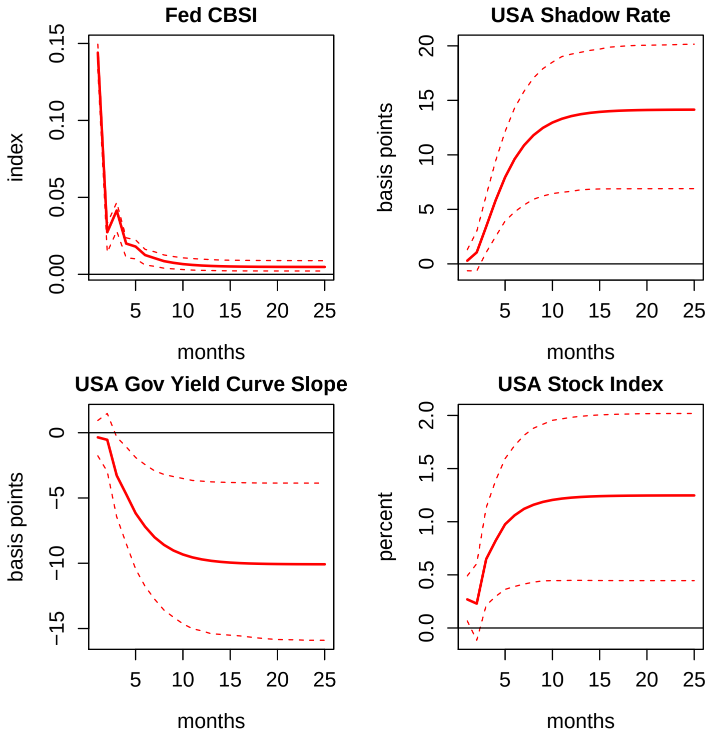
[14] For the Bank of Japan we utilized the Policy Rate due to lack of available data. Source: Refinitiv.

[15] The Euro Stoxx 50 for the Eurozone, the S&P 500 for the USA, the FTSE100 for the UK and the Nikkei 225 for Japan. Source: Refinitiv.

[16] It is the difference between the 10-year and the 3-month government bond yield. Source: Refinitiv.

three months. Instead, for the Eurozone we observe mixed responses: the effect on the shadow rate is positive and statistically significant; the yield curve slope is negatively affected after a couple of months, while the response of the stock index becomes statistically insignificant after six months. Probably these responses are due to the heterogeneous composition of the Eurozone (a monetary union of “core” and “peripheral” member states).

Figure 7: Impact of Positive shock to CBSI on USA



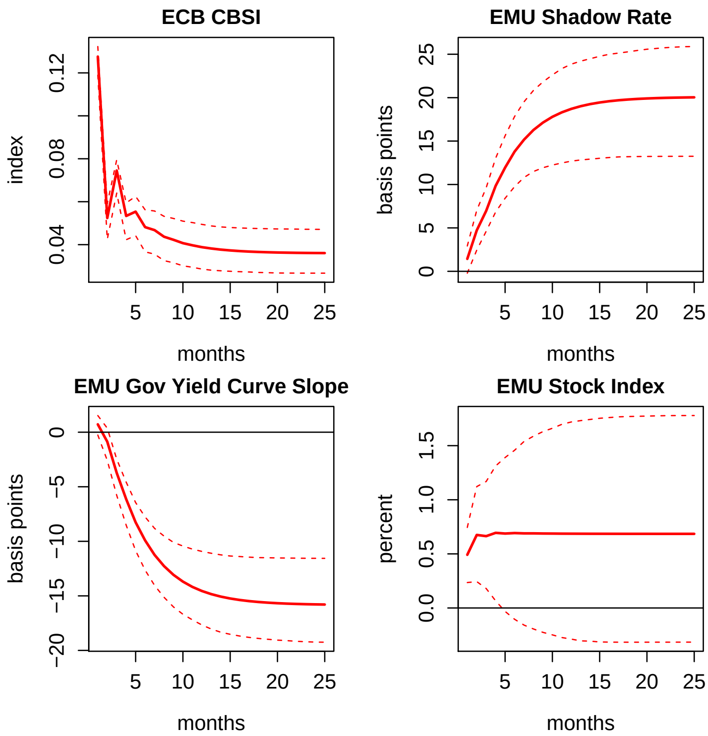
Notes: GIRFs confidence interval at 68%.

4.2 Central bank connectedness

4.2.1 Network Methodology

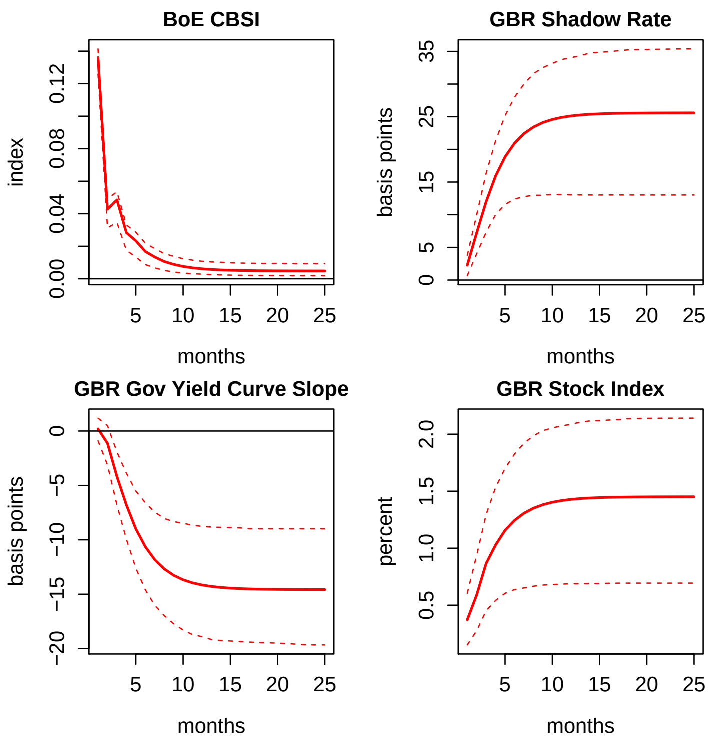
After having conducted the GIRFs analysis we investigate whether and to what extent Central Banks influence each other through their communication. We do this by estimating a network for our monthly CBSIs. Modern network theory consists in applying graphs to represent *connectedness* between objects. In economic research, a network is a representation of interconnection between entities or countries, which can be derived with different econometric approaches. Billio et al. (2012) concentrate on univariate models using pairwise Granger causality and obtain a static and directional adjacency matrix without a measure of spillover (the edges assume values 0 or 1). Diebold and Yilmaz (2015) employ the Generalized Forecasted Error Variance Decompositions (GFEVD) from a time-varying VAR model (OLS estimation with a fixed rolling window) to assess dynamic *connectedness* between entities. This approach returns a directed adjacency matrix but does not discriminate against negligible connections. To overcome these drawbacks, we propose a two-step approach. First, we apply the Network Estimation for Time Series (NETS) methodology (Barigozzi and Brownlees, 2019) to get a directed adjacency matrix identifying the relevant interconnection among CBSIs based on Multivariate Granger causality. Then, following the Diebold and Yilmaz (2015) approach we assess the spillover effect for each couple of vertexes previously detected with NETS (in our network representation the thickness of the edge indicates the degree of spillover and the arrowhead symbolizes direction). Finally,

Figure 8: Impact of Positive shock to CBSI on Eurozone



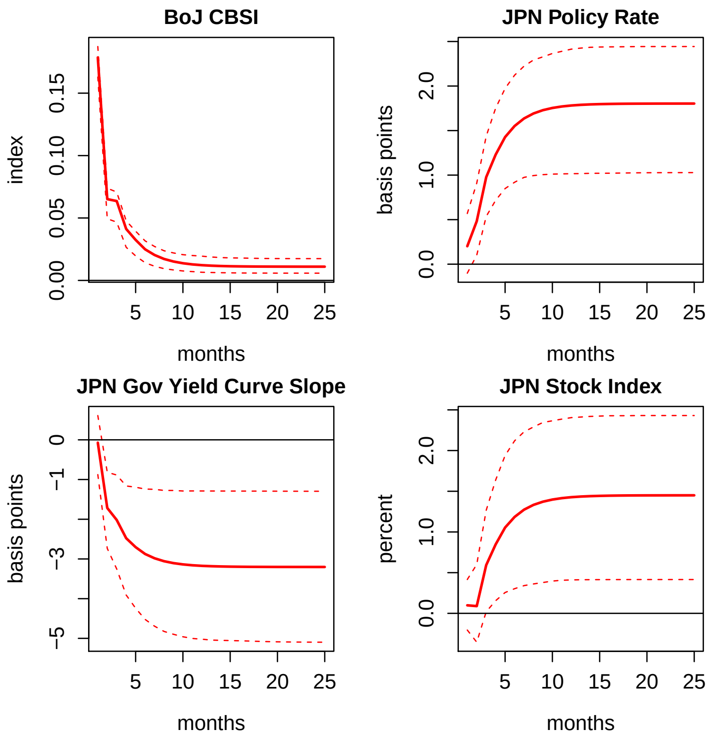
Notes: GIRFs confidence interval at 68%.

Figure 9: Impact of Positive shock to CBSI on UK



Notes: GIRFs confidence interval at 68%.

Figure 10: Impact of Positive shock to CBSI on Japan



Notes: GIRFs confidence interval at 68%.

starting from January 2006 we iterate[17] our two-step approach to assess time-varying statistically significant connectedness and spillover effects among central banks' communication.

The NETS methodology performs network analysis on a large panel of time series. This approach assumes a zero-mean stationary $p-th$ order Sparse VAR, meaning that both the inverse covariance matrix of the innovations (also known as *concentration matrix* assumed positive definite) and the autoregressive coefficient matrices are assumed to be sparse:[18]

$$Y_t = \sum_{q=1}^{Q} A_q Y_{t-q} + \epsilon_t, \quad \epsilon_t \sim iid\left(0, C^{-1}\right). \tag{5}$$

With the application of a new LASSO algorithm, the approach allows to jointly estimate and detect the non-zero entries of the autoregressive matrices and the concentration matrix.

As a reminder, the multivariate Granger causality (which is the standard notion of dynamic interdependence used for time series) states that y_j Granger cause y_i if the first variable reduces the Mean Squared Forecast Error of the second one. Formally,

$$j\ GC\ i\ if\ \underbrace{E\left[\left(y_{i,t+h} - E\left[y_{i,t+h}|y_{1,t},...,y_{N,t}\right]\right)^2\right]}_{\text{MSFE with } j} < \underbrace{E\left[\left(y_{i,t+h} - E\left[y_{i,t+h}|y_{1,t},...,y_{N,t} \setminus y_{j,t}\right]\right)^2\right]}_{\text{MSFE without } j}. \tag{6}$$

As suggested by the authors, it is immediate to see that 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

[17]We add a new observation to a pre-specified starting sample (January 2000-December 2004) and we update the framework estimates.
[18]In general, the sparsity assumption can be referred to contemporaneous and lead/lag dependence structure of the system.

Granger causality, i.e. no connectedness between two entities.

We then determine the degree of spillover between central banks - represented by the thickness of the edges in the graph - using the GFEVD (Pesaran and Shin, 1998) derived from a Sparse VAR in line with the approach of Diebold and Yilmaz (2015).

Starting from the stationary Sparse VAR model presented above we can find its infinite moving average (MA) representation:

$$Y_t = \sum_{q=0}^{\infty} \phi_q \epsilon_{t-q} \; where \; \phi_q = A_1 \phi_{q-1} + ... + A_Q \phi_{q-Q}. \tag{7}$$

We then obtain the GFEVD, which allows to discern the contributions of each variable to the variance of the forecast error H steps ahead,[19] in the following way:

$$\Theta_{i,j}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \phi_h \Omega e_j)^2}{\sum_{h=0}^{H-1} (e_i' \phi_h \Omega \phi_h' e_i)}, \tag{8}$$

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

4.2.2 Static and Dynamic Communication Network

Figure 11 shows the results for the full sample network analysis. As can be noted from the left-hand side graph, the Fed and the ECB seem to influence all other banks, whereas the BoE does not influence the BoJ. In addition, it seems that the BoJ generates and receives lower spillovers, as can be inferred from the thinner edges. Unsurprisingly, the Fed and the BoE are strongly interconnected, and it is worth pointing out that also the BoE highly influences the Fed. In effect, the interconnection between these two banks is the highest. Moreover, the ECB shows interconnection with the other banks but it is not very strong.

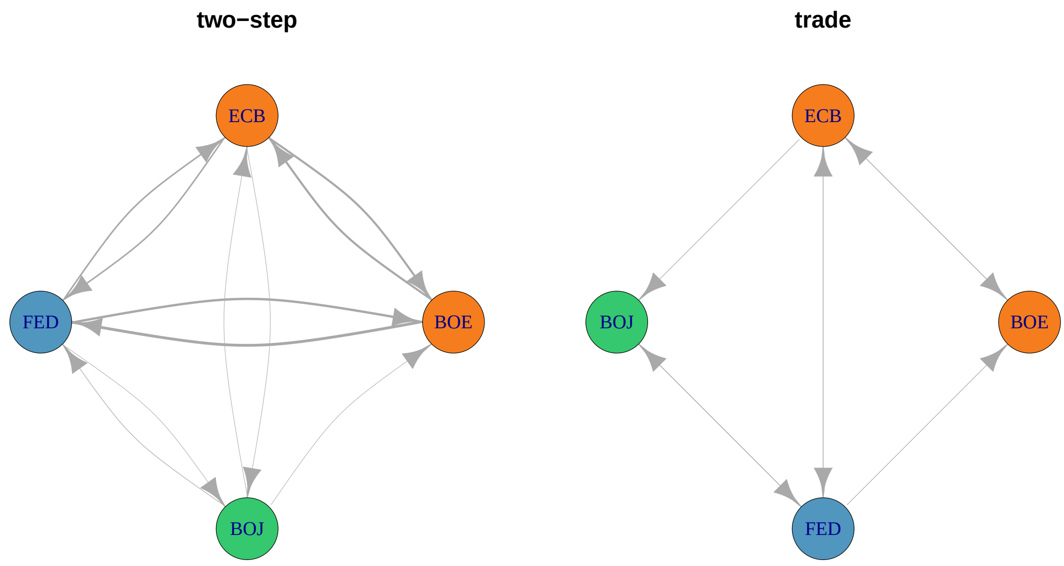
As previously mentioned, we include a comparison with a directed network derived from trade relationships, following the framework adopted by Armelius et al. (2020). Hence, starting from trade flows in 2019 (IMF Direction-of-Trade Statistics) for the countries of interest, we build our trade network in the following way: 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.

As can be inferred from the right-hand side graph in Figure 11 our trade network partly differs from the one based of the CBSIs. Indeed, even though the UK is not among the first five trade partners of the USA, BoE's sentiment seems to influence the Fed's. Moreover, Japan is not one of the key trade partners of the Eurozone; still, the BoJ influences the ECB. It is also striking that there is not a strong trade connection between the UK and Japan, nevertheless BoJ's communication influences BoE's sentiment. One possible conclusion that can be drawn from these results is that the importance of a country's Central Bank in influencing other institutions' communication is not always commensurate to its relative economic importance. Other factors might play a role: such as the reputation of the institution or political and historical reasons, as it is the case for the interconnection between the Fed and the BoE.

Overall, our findings are partly in line with Armelius et al. (2020), who suggest that the Federal Reserve has a significant impact on other banks in terms of sentiment and that the ECB communication is less relevant. Nevertheless, our analysis seems to show a strong influence of ECB on other central banks' sentiment. Two possible explanations could be related to: (i) the computation of the

[19]We chose 3 steps ahead as forecast horizon, but as robustness check we got similar results with different steps.

Figure 11: CBSIs from our two-step approach vs trade networks



sentiment index; (ii) the different Granger causality test performed in our analysis. Armelius et al. (2020) smoothed their indices with a 40-period moving average, getting very persistent indicators, whereas we avoided any sort of smoothing. In addition, we run a multivariate Granger causality test instead of a pairwise one.

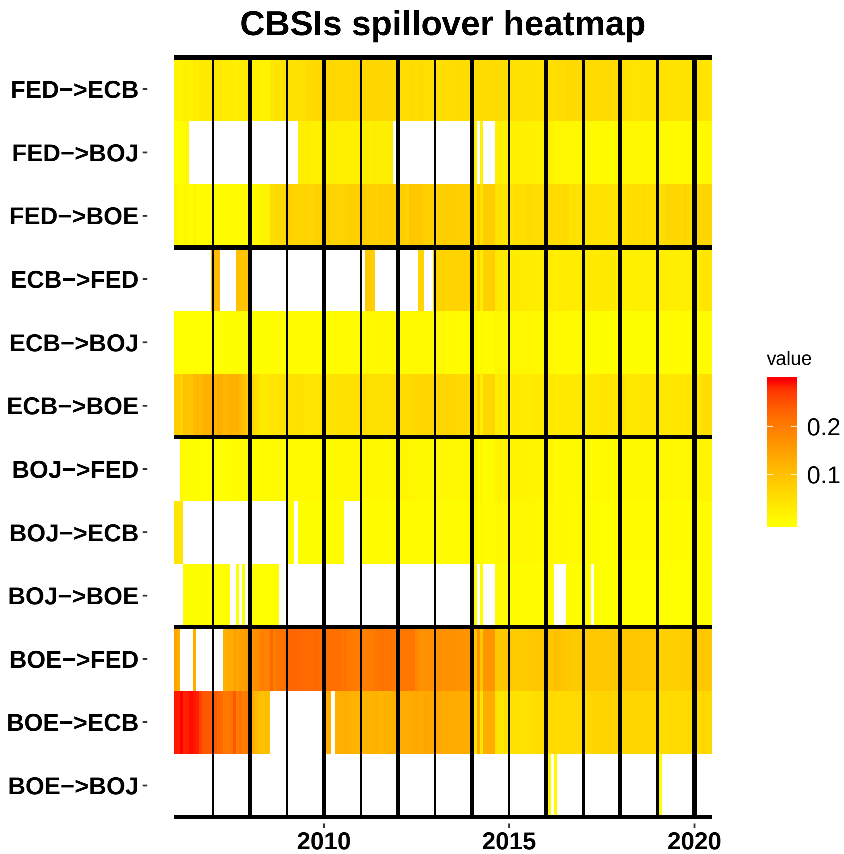
For the second part of our network analysis, that is the dynamic one, we present the time-varying spillovers with a heatmap (Figure 12). The spillovers are shown on the vertical axis and the time horizon on the horizontal axis. Overall, the heatmap describes the pattern of interaction between central banks in terms of sentiment over the period of analysis (statistically significant connectedness and relative spillover effect).

The first result worth mentioning is that the main source of GFEVD of each CBSI is endogenous, meaning that the central bank sentiment is mainly affected by domestic economic conditions (business cycle, prices, unemployment, sovereign and banking risks). Nevertheless, the spillover effects by other central banks' communication is sizable (on average around 15 percent excluding BoJ).

The Fed seems to influence the ECB almost for the whole period of analysis. The same holds for the impact on the BoE, with a slightly higher magnitude. Considering the effects on the BoJ, it is noteworthy that spillover effects disappear between 2006 and 2009 and from 2012 to 2016. Overall, the most important finding seems to be that in the aftermath of the financial crisis Fed's communication affected other banks more than during the preceding and following years. This seems to be evidence of the Fed having a leading role in managing the post crisis environment with (un)conventional monetary policies. Indeed the Fed was the first institution to adopt QE measures in response to the financial crisis, paving the way for other central banks to intervene in a similar way.

Instead, the ECB seems less important in influencing the Fed, with spillover effects that start to materialize significantly only in the second half of the 2010s. This fact is observable also in the different path of monetary policy in the first half of 2010s: while the Fed started to adopt tapering measures already in 2013, the ECB did not decrease its support to the economy through its unconventional monetary policy. Hence, with different policies implemented and without perfectly synchronized business cycles, it may not be a surprise that the Fed was not affected by the ECB communication. Spillovers effects on the BoJ are instead quite stable for the whole period; whereas connectedness with the BoE is particularly high before the financial crisis, afterwards it is still high but less so.

Figure 12: CBSIs Spillovers Heatmaps



Notes: $A \to B$ denotes the spillover effect from A to B conditional to multivariate Granger causality.

Regarding BoE's spillovers, we observe a strong influence over both the Fed and the ECB; however, if spillovers towards the former are the highest during the financial crisis, for the latter the opposite is true. It appears that the ECB was more influenced by BoE's sentiment in the period before the financial crisis and in the immediate aftermath, but not during the crisis. Moreover, it might be argued that the entire Brexit process had an impact on BoE's communication, decreasing the magnitude of the spillovers from the BoE to the other central banks. Lastly, there are almost no spillovers on the BoJ.

Finally, for the BoJ we find low connectedness with the ECB and the Fed for the whole period of analysis, with some gaps, whereas spillovers towards the BoE disappear for several years (from 2009 to 2016). Altogether, these findings suggest a lower degree of influence of the BoJ on other central banks' communication. These lower spillovers might be caused by a different path of monetary policy: indeed, the BoJ had to face a "liquidity trap" and deflationary pressures already before the financial crisis, whereas other central banks did not.

5 Conclusions and Further Research

Without doubt, communication by central banks is an important monetary policy tool. Many researches have empirically demonstrated that it can influence financial and macroeconomic variables (Rosa, 2011; Kurov, 2012; Fratzscher, 2008; Égert and Kočenda, 2014; Ehrmann and Talmi, 2020; Jubinski and Tomljanovich, 2017).

Following the latest literature in the field of Natural Language Processing (NLP), we develop a sentiment index for central banks (Fed, ECB, BoE, BoJ), starting from official documents, to assess how it affects financial variables, both domestic and international ones through spillovers effects. We therefore focus also on patterns of interconnection and spillover effects among central banks' communication.

With a large dataset that comprises speeches and press releases, we compute a sentiment index for each central bank (CBSIs). We show that our CBSIs behave somehow differently but share common trends (e.g. they decrease during the Great Recession and during the Covid-19 crisis). In addition, from the analysis of our word clouds generated by the Tdf-If function, we observe that banks might share common communication patterns; nevertheless, we also notice some differences in the rank of words for each institution.

Furthermore, through VECMs and GIRFs analysis we find that the way a central bank communicates has a significant impact and with the expected sign on financial variables (positive for shadow rate and stock index, negative on yield curve slope), in line with the existing literature (among the others, Armelius et al., 2020). In particular, for the USA, the UK and Japan the aforementioned effects become statistically significant within three months. Instead, for the Eurozone we observe mixed responses.

Finally, we propose a two-step approach to detect the relevant interconnections among central banks' sentiment index via NETS, the novel LASSO shrinkage estimator defined by Barigozzi and Brownlees (2019) and to assess sentiments' spillover effects from a Generalized Forecast Error Variance Decomposition (GFEVD) following the framework of Diebold and Yilmaz (2015). The outcomes are the following. In term of adjacency matrix, as in Armelius et al. (2020), we find that sentiment connectedness can differ from trade flows connections. Although domestic economic conditions affect the central bank communication, the sentiment indices generate time-varying spillovers over each other: for instance, Fed's spillovers intensified after the Great Recession, whereas the Bank of Japan seems to marginally affect the others, possibly because of different policy objectives across the period of analysis. We also note that after 2016 Bank of England's spillovers slightly diminish, perhaps because of Brexit and its consequences on BoE's communication.

We believe that further research may be relevant. One possible shortcoming of a Sentiment Index based on official publications by central banks is the lack of available data for the very short run (i.e. less than a month). Some researchers acknowledge the growing importance of social media for political and financial communication. Indeed, inside the literature there is an emerging field of analysis concerning social media communication by policy makers and market actors. In particular, Camous and Matveev (2019) and Bianchi et al. (2019) suggest that there is a link between tweets by the US President Donald Trump and market expectations on the Fed monetary policy: they find a strong and negative correlation between Trump's tweets advocating for lower interest rates and Federal Funds Futures. With a similar methodology based on tweets, Masciandaro et al. (2020) try to capture central banks' ability to surprise the markets. They proxy the market sentiment on monetary policy from tweets by market participants, then they calculate the distance between this indicator and an indicator based on official transcripts by central banks, naming this indicator "Central Bank Surprise Index". Therefore, another possible research project could be investigating the impact of central banks' sentiment on the sentiment embedded in economic news or in tweets by market participants.

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6 Appendix

Table 2: CSBI summary statistics, overall vs subsamples

	Period	Fed	ECB	BoE	BoJ
Mean	2000-2007	-0.13	-0.02	-0.23	-0.23
	2008-2010	-0.32	-0.20	-0.39	-0.30
	2011-2020	-0.22	-0.23	-0.31	-0.19
	2000-2020	-0.20	-0.15	-0.29	-0.22
Standard Deviation	2000-2007	0.12	0.10	0.11	0.24
	2008-2010	0.09	0.11	0.10	0.12
	2011-2020	0.12	0.10	0.10	0.13
	2000-2020	0.13	0.14	0.12	0.18

Table 3: Dataset summary statistics

country	variable	source	mean	min	max	sd
USA	CBSI	Prometeia	-0.20	-0.55	0.16	0.13
	Shadow rate	Refinitiv	1.31	-2.99	6.54	2.43
	Log Equity Index	Refinitiv	7.30	6.63	8.06	0.34
	Slope Government Bond Curve	Refinitiv	1.77	-0.62	3.68	1.15
EMU	CBSI	Prometeia	-0.14	-0.48	0.19	0.14
	Shadow rate	Refinitiv	0.16	-7.82	5.01	3.44
	Log Equity Index	Refinitiv	8.07	7.60	8.58	0.21
	Slope Government Bond Curve	Refinitiv	1.23	-0.17	3.12	0.75
GBR	CBSI	Prometeia	-0.29	-0.64	0.07	0.12
	Shadow rate	Refinitiv	0.12	-6.51	6.05	4.21
	Log Equity Index	Refinitiv	8.66	8.20	8.95	0.18
	Slope Government Bond Curve	Prometeia	0.92	-1.01	3.42	1.15
JPN	CBSI	Prometeia	-0.22	-0.71	0.33	0.18
	Policy Rate	Refinitiv	0.08	-0.10	0.50	0.16
	Log Equity Index	Refinitiv	9.52	8.95	10.07	0.31
	Slope Government Bond Curve	Refinitiv	0.87	-0.11	1.86	0.48

Note: time span January 2000-December 2019, monthly frequency data.