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The Communication Reaction Function of the European Central Bank. An Analysis Using Topic Modelling

Luca Alfieri, Diana Gabrielyan*

Abstract

In this paper we analyse the communication reaction function of the European Central Bank (ECB) through topic-based indices derived from the speeches of the central bank. These indices are used as dependent variables in policy and communication reaction function models, as suggested by recent literature. The topics are extracted using Latent Dirichlet Allocation (LDA), a popular text mining algorithm for topic extraction. The ECB is at present reviewing its monetary policy strategy, and scholars are incorporating the new methods offered by text analysis to study the policy reaction function of the bank. We show how indices built through topic modelling can be used to study the communication reaction function of a central bank, and we analyse which variables are significant for every topic communicated by the ECB.

Keywords: Monetary policy, Central banking, Text mining, Communication reaction function.
JEL Classification: C55, C22, E52, E58.

The views expressed are those of the authors and do not necessarily represent the official views of Eesti Pank or the Eurosystem.

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Non-technical summary

The European Central Bank has recently revised its monetary policy strategy. Such revisions have in the past led to extensive studies being run on the ECB policy reaction function, and scholars have estimated the policy reaction function of the ECB using various empirical models derived from the literature on optimal monetary policy and general information provided by the ECB itself. Text mining has sparked increased interest in research into central banking issues. A growing macroeconomic literature uses text mining to study the policy communication of central banks, with most papers using textual data to increase the amount of information for the model estimates. There are other applications of text mining, such as using textual data from the ECB's introductory statements to build indices for understanding the degree of tolerance towards inflation and deflation or using ECB communication to estimate its approach to interest rate setting. Most papers aim to connect "words and deeds" (Cour-Thimann & Jung, 2020, p.10; Gerlach, 2007, p.1) and so the policy reaction function and the communication reaction function must be consistent with each other, so that the researchers can use the variables of the policy reaction function to estimate the communication reaction function of a central bank.

In this paper, we use topic modelling to extract topics from the speeches of the ECB. Topic modelling means using machine learning methods to detect specific topics in different documents. The topics are transformed into indices and become new variables for estimating how the ECB's communications react to the particular information that is available.

We aim to fill the gap in the literature on the communication reaction function and topic modelling. The paper determines whether the topic indices are useful in estimating the communication function of the ECB in more detail than previous studies that employ sentiment analysis or discrete indices do. For textual data, we use a dataset of public speeches by the ECB, which includes speeches from ECB presidents, vice-presidents and board members. The data are updated every two months and can be downloaded from the ECB website in csv format, and our dataset contains data from 1997 until January 2020. We purposefully do not consider data after that date so that we can exclude the effects of Covid-19.

From an empirical point of view, the dataset of speeches undergoes a number of pre-processing transformations, which are standard in the literature. The topic modelling technique we use is a probabilistic topic distribution method, and we test different variations of the models to determine the optimal number of topics and the topics themselves. This also allows us to reduce the arbitrariness in the choice of the number of topics, and so we extract five relevant topics from the ECB speeches. These topics are used to create five topic indices, each containing the cumulative frequency of the most commonly occurring words in that topic over time. These topic indices are regressed by inflation, and taken as projections of the ECB and quarterly one year ahead forecasts from the Survey of Professional Forecasters.

Our results show that the topic indices extracted from the speeches of the ECB can provide more detailed analysis than studies based on discrete dependent variables or simple tone indices can. Our topic indices also add new insights into the communication reaction functions of central banks and allow us to observe the impact of the significant variables in all the aspects of the communication reaction function. Some of our findings are in line with the literature, but there remain limitations caused by the difficulty of interpreting the signs of the coefficients, the possible risk of misspecification caused by the presence of non-linearity or asymmetry in the ECB loss function, and some statistical issues related to non-stationarity.

The paper contributes to the literature that combines macroeconomic models and text mining methods to derive topic indices in an unexplored environment. In addition, our study describes novel findings that are relevant to the literature on the communication reaction function. Using the topic indices approach allows us to treat the communication reaction function not as a monolith but in a multifaceted framework. Finally, the paper adds new insights to the studies on the connections between communication and the policy reaction function.

Contents

1 Introduction

There is renewed interest in studies about the policy reaction functions and communications of central banks because of the new opportunities offered by text mining methods. However, literature analysing the communication reaction function is still scarce. The European Central Bank started a new revision of its monetary policy strategy in 2020, and similar revisions have in the past contributed to studies of the ECB policy reaction function (Gerlach, 2007; Carstensen, 2006).

The central bank does not explicitly share the way that its decisions are taken, and thus researchers have estimated the policy reaction function of the ECB using different empirical models from the literature on optimal monetary policy, previous empirical research, and general information provided by the ECB itself (Cour-Thimann & Jung, 2020; Rivolta, 2018; Gerlach & Lewis, 2014).

Recently developed methods that use the text mining approach are currently being actively exploited by macroeconomists, particularly by those focused on central banking (Hansen et al., 2019; Hansen & McMahon, 2016). Papers on the reaction function of the ECB usually use texts coming from the communications of the central bank to add new independent variables so they can increase the amount of information in their models and connect the words of the ECB with its actions (Cour-Thimann & Jung, 2020; Gerlach, 2007).

There is also a plethora of studies focusing on other applications of text mining. Paloviita et al. (2020) for example create a sentiment index from the introductory statements of the ECB to understand the symmetry or asymmetry of the loss function of the bank to the risk of inflation or deflation. Cour-Thimann and Jung (2020) use an ordered probit model to estimate the interest rate setting of the ECB by deriving two discrete variables, one of which is related to the risk to price stability and the other of which relates to the risk to growth. These variables are then added as independent variables and later as dependent variables to estimate the communication reaction function of the ECB. If the ECB's words and actions are connected, the policy reaction function and the communication reaction function must be consistent with each other, so the same variables as for the policy reaction function can be used to estimate the communication reaction function of a central bank.

Our research aims to fill the gap between the literature on the communication reaction function and that on topic modelling. The paper particularly aims to determine if the topic indices can be useful for estimating the communication function of the ECB in more detail than previous studies employing sentiment analysis or discrete indices could. For this we first use Latent Dirichlet Allocation (Griffiths & Steyvers, 2004; Blei et al., 2003) to extract topics from the ECB speeches and then we use common quantitative techniques to transform them into indices. These newly formed topic-based indices are the new dependent variables for estimating the communication reaction function.

The paper contributes to the literature that combines macroeconomic models and text mining methods by deriving topic indices in an as yet unexplored environment. Moreover, our study describes novel findings that are relevant to the literature on the communication reaction function. Using topic indices lets us treat the communication reaction function not as a monolithic entity, but in a multifaceted framework. Finally, the paper adds new insights to the studies on the connections between communication and the policy reaction function.

From the empirical point of view, we pre-process the texts following the standard procedure in the literature on text mining. Estimating different LDA models and conducting various robustness checks lets us determine the optimal number of topics. Using this number, we create the topic-based indices and regress them using model specifications provided in previous studies (Cour-Thimann & Jung, 2020; Hartmann & Smets, 2018). On top of this we consider the effects of the Great Recession and the importance of the zero lower bound after June 2014. As a last step, we perform a number of robustness checks on the regression results.

The first section of the paper describes the literature on the subject. The second section illustrates the text analysis process, the data used, and the models estimated. The third section presents the topics derived and the results of the regressions. Finally, the fourth section describes the results.

2 Literature Review

This section reviews the literature on central bank communications and the development of topic indices, then discusses papers studying the policy reaction functions of the ECB. We also review the literature that connects policy reaction functions and the external communications of central banks.

Several papers employ text mining methods to study central bank communication and derive topics from the speeches. One example is Hendry and Madeley (2010) who use Latent Semantic Analysis on communication by the Bank of Canada and observe what type of information can affect returns and volatility in interest rate markets. El-Shagi and Jung (2015) show that the minutes of Bank of England's Monetary Policy Committee influence the expectations of the markets for future monetary policies. Hansen and McMahon (2016) and Hansen et al. (2019) use text mining methods to study the macroeconomic effects of the Fed's external communications. Lehtimäki and Palmu (2019) create a topic-based indicator, that measures the predictability of monetary policy through the official comments by policy makers. Thorsrud (2020) constructs a new business cycle index based on quarterly GDP growth and information from a daily business newspaper found through a text mining algorithm. Their index can detect what type of news is more related with economic fluctuations. These studies, however, use the indices solely as independent variables and aim to measure their effects on macroeconomic indicators. The number of papers employing indices as dependent variables is still limited.

Studies of the ECB's policy reaction functions started with the beginning of the European Monetary Union (EMU) and the creation of the ECB. Carstensen (2006) shows through ordered probit models how the growth of M3 has been of central importance since the beginning of the EMU. Moreover, he argues that the ECB is more prone to agreeing to raise the interest rate rather than to agreeing to cut it. This implies that the anti-inflation view is stronger than the anti-deflation one.

Gerlach (2007) also applies an ordered probit model, using the ECB Monthly Bulletin to construct indices for evaluating the policy reaction function and shows that the ECB reacts to real activity, M3 and the exchange rate but not to inflation. In Gerlach's view, this happens because the ECB interprets the inflation shock as temporary, but actually the reaction of real activities is stronger because it is related to the inflation outlook. In other applications, Gerlach and Lewis (2014) use macroeconomic forecasts from the Survey of Professional Forecasters (SPF), which is available from the ECB, to estimate its policy reaction function and the influence of the crisis and the zero lower bound through a smooth transition model.

Mirkov and Natvik (2016) study the relationship between the forward guidance communications of central banks and forecasts. They show how the past and present forecasts of the central banks are connected. Adherence to the forecast makes the forward guidance of the central banks more effective. However, Gosselin et al. (2008) argue that a lack of full information from the central bank can diminish the effects of forward guidance and the alignment in expectations between the central bank and the private sector. Angelini et al. (2019) stress the important effect of technical assumptions such as the assumption for fiscal development in the euro area, and of judgmental information on the ECB's projections.

Rivolta (2018) examines the policy reactions of the ECB over the period 1999-2014 and investigates whether changes can be observed after the financial crisis of 2008 by employing various financial and macroeconomic variables. Most of this literature considers the importance of studies on optimal monetary policies such as Taylor (1993), Clarida et al. (1998), Orphanides (2001), Orphanides (2003), Orphanides (2011) and Orphanides and Wieland (2013) to make proper estimations of the policy reaction function. The Orphanides rule in particular is considered to be the one applied by the ECB, even if it there is still some debate about whether the rule is valid with the new unconventional policies of the bank (Hartmann & Smets, 2018; Orphanides & Wieland, 2013). It has to be noted, that numerous papers in this literature use macroeconomic forecasts in real time for inflation and GDP growth instead of unobserved future inflation and output. In principle, the communications and policy reaction function should be consistent with each other, so it may be feasible to replace indicators of interest rates with topic indices and to regress those indices using the same variables and specifications that are in the models for the policy reaction function.

An increasing body of literature is now relating text mining analysis to the analysis of policy reaction functions, loss functions, and the introduction of new goals by different central banks during past decades. Dieijen and Lumsdaine (2019) use LDA and a Dynamic Topic Model (DTM) to observe whether and how much the US Federal Reserve (the Fed) balanced its policies from 1997 to 2016 between the two components of its dual mandate of full employment and control of inflation. Moreover, they check whether the Fed added a third goal after the financial crisis of 2008-09, targeting financial stability and systemic risk. In their work the authors use the speeches from the Federal Reserve and extract three topics with LDA. They find that after the crisis the Fed did indeed give more weight to employment, though the greater priority before the crisis had been inflation. In addition, they observe that the crisis has led the Fed to add financial stability and avoiding systematic risk as a third goal.

Among other papers that take the topic modelling approach to textual data is Klejdysz and Lumsdaine (2020), where LDA is applied to extract six topics from the introductory statements and Q&As of the ECB (2004-2018) and analyse their effects on volatility in the stock market. Event-based regressions are estimated, and the press conferences are disentangled between the ECB's presidencies of Mario Draghi and Jean-Claude Trichet. The findings suggest that communication by the ECB is related to the monetary policy stance and the communication is informative for the market. In consequence, any changes in the communications of the ECB can imply greater uncertainty in the financial markets. Hartmann and Smets (2018) show how ECB topics evolved in 1999-2018 through fifty LDA topics in the speeches of the ECB and the Supervisory Board of the Single Supervisory Mechanism at the ECB. These fifty topics are subsequently aggregated into nine large macro areas and the policy reaction function of the short-term interest rate is estimated using the ECB and SFP macroeconomic projections. The deviation from the inflation target is inserted, as is the deviation of forecast GDP growth from the potential output. The paper finds that the macroeconomic projections and the deviation of inflation are both significant in determining the policy reaction function of the ECB. The model is based on Orphanides (2003). A similar method of extracting topics with LDA together with sentiment analysis allows Kaminskas et al. (2021) to investigate the effects of ECB communications on financial data.

Paloviita et al. (2020) use the macroeconomic projections of the ECB and the introductory statements of the ECB to check for the presence of symmetry or asymmetry in the face of inflation and deflation. They construct an index to detect the tone of the different texts and estimate the loss function, considering an optimal monetary policy. As a robustness check LDA is used and two topics related to price stability are extracted out of the nine available. The results differ depending on what target inflation rate is assumed.

Cour-Thimann and Jung (2020) estimate ordered probit models using twenty years of data from the ECB to derive the central bank's policy functions. The models are implemented by adding variables created from the ECB's introductory statements at ECB press conferences, and the KOF Monetary Policy Communicator. The variables represent risks to price stability and to growth. In the models, the dependent variables are replaced with their two discrete communication variables, and the results highlight that communications variables are partially explained by the projections of the ECB and the Survey of Professional Forecasters, the M3 annual growth, and the Fed funds policy rate target, as well as other regressors such as oil prices. Cour-Thimann and Jung (2020) base their theoretical framework on forward-looking Taylor rules (Orphanides, 2001).

Our paper takes account of these recent studies and exploits the possibilities offered by the LDA topic models to create topic indices. The aim is to fill the gap between the studies on communication reaction functions and those on topic modelling.

3 Empirical Analysis

3.1 Text Analysis and Topic Indices

The public speeches of ECB presidents, vice-presidents and board members (ECB, 2019) have recently started to be published on the ECB website in CSV format and openable for use by anyone. The dataset that is available stretches back to 1997 and is updated every two months. The dataset of speeches released by the ECB includes press conferences held in the ECB headquarters or in other institutions. The speeches are published a few times a week and for the purposes of our analysis they are aggregated by quarters. We consider the entire dataset from February 1997 to January 2020 and so deliberately exclude the effects of Covid-19.

The first step for our empirical analysis is to create topic indices. This section describes the different procedures used to define the number of topics in the LDA model and the methods used to aggregate the useful terms into topics. This step is needed to make the choice of the number of topics less arbitrary.

We start the analysis of the ECB speeches with initial pre-processing operations such as erasing the non-English speeches, punctuation, stop-words, white spaces and digits. We then proceed to tokenise the sentences, which means splitting them into individual words, so that “high interest rates” for example becomes the three tokens “high”, “interest” and “rates”. After the words have been tokenised, we stem them. This is done by cutting off the beginning or the ending of a word to reduce their length, so that “policies” becomes “polici” or “financial” becomes “financi”, and uniting similar words. In the last pre-processing step we eliminate the words that do not add any additional meaning, having already eliminated the standard language-specific stop-words in previous steps. The words we now eliminate are those like “take”, “year” “today”, “part” and so on.

Following the pre-processing stage, we employ a term frequency-inverse document frequency, or TF-IDF, (Salton & Harman, 2003) to see what the most frequent terms in each document in the corpus are, to observe what other words can be excluded, and to find which n-grams[1] can add more interpretation on the topics. We separate words by choosing those with a minimum document frequency between 10% and 90%. TF-IDF removes any words that occur in fewer than 10% of the documents, highlighting that these words do not contain relevant information and are therefore not often used in ECB speeches. TF-IDF can be described as:

$$TF-IDF = tf(w,d) \times log(\frac{N}{df+1}), \tag{1}$$

where $tf(w,d)$ counts the number of times the word w appears in document d. The denominator of (1) is the IDF. This takes on a value between 0 and 1 and measures

[1]The term n-grams in text analysis is used for two or more words that are contiguous and have a specific meaning in the texts.

how common a word is in the corpus by how frequently it appears. N is the corpus, the set of the documents in the dataset, and df is the occurrence of one term in the document set: the closer df is to 0, the more common the word is, and if the measure is close to 1, the word appears only rarely.

The TF-IDF results show that only 25 of the 258 bigrams and trigrams are particularly relevant for TF-IDF measurement, and these do not add particular value to the interpretation of the topics[2]. In consequence we choose to limit our analysis to unigrams and bigrams and continue with LDA. LDA is a probabilistic Bayesian version of the Latent Semantic Analysis (LSA), but it allows a greater level of accuracy than LSA. It identifies each document analysed as a mixture of topics, and it clusters the words into relevant topics. The algorithm assigns different probabilities to each word and document by estimating their probability distribution. The joint distribution for the LDA algorithm can be summarised as follows:

$$P = (\theta_{1:M}, z_{1:M}, \beta_{1:k} | N; \alpha_{1:M}, \eta_{1:M}), \tag{2}$$

where M is the number of documents that are the object of the analysis, k is the number of topics, θ is the distribution of the topics for each document, z is the number of topics per document, β is the distribution of words in each topic, and N is the corpus or the collection of documents in the dataset composed of all the M documents. α and η are vector parameters, with α relating to the distribution of the documents and η to topics. The LDA model estimates the joint posterior probability of θ, z, and β.

We apply LDA with a simple document matrix and follow the methods of Blei et al. (2003), and Griffiths and Steyvers (2004), but use only unigrams or bigrams. In those papers the most robust result is provided by the Griffiths and Steyvers (2004) model, in which Gibbs sampling is applied (Geman & Geman, 1984) and bigrams are used.

To validate this result, and also the number of topics, we run different robustness checks. Firstly, we perform the LDA with both bigrams and unigrams setting 4, 5, 14 and 50 as the number of topics. The limit of 50 topics is based on the findings of Hartmann and Smets (2018) and the similarity between our dataset and their data. We chose 4 and 5 as the number of topics as a rough guess based on preliminary visualisations of the results of the LDA models. The number 14 is introduced as a further check in a subsequent run of the algorithm given the results of the first run of the estimations. We compute perplexity[3]and coherence scores as two typical measurements used in LDA literature, along with data visualisation tools[4]. The higher the coherence score

[2]The list is available upon request.

[3]A typical score used in LDA as shown in Blei et al. (2003). We specifically use the log-perplexity method provided by Python's gensim package.

[4]As a coherence score, we employ the one suggested by Röder et al. (2015). The perplexity score measures how well the natural language processing-based probability model can predict a sample. The perplexity score is the inverse probability of the test set normalised by the number of words in the same set. The lower the level of perplexity is, the better the model is. The coherence score meanwhile measures the degree of semantic similarity between the most important words in a specific topic.

is, the better the model is, so the two score measures work differently and in opposite directions (See Table 1). The results of the coherence scores are better visualised in Figure 1[5].

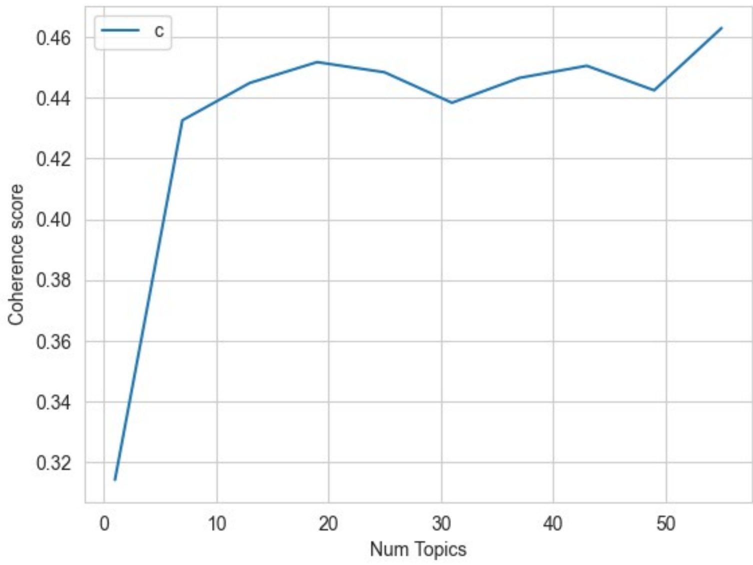

Figure 1: Coherence scores of LDA models with different numbers of topics

Data source: ECB (2020)

It is apparent from analysing the results from Table 1 and Figure 1 that the best choice is to have four or five topics. Having 50 or 14 topics gives the best results in Table 1, but Figure 1 shows this is not a good choice because the first spike of the curve is at fewer than 10 topics. Furthermore, data visualisation with 50 or 14 topics does not separate out the different topics efficiently. We can find confirmation of this by observing the intertopic distance maps of 14 topics and 50 topics (see Sievert and Shirley (2014) and Figures 2 and 3). The map represents the topics as spheres on a cartesian plane. The more distant the topics are from one another, the fewer words they have in common. The distance itself is found using the Jensen-Shannon divergence, which is able to distinguish between two or more distributions and is based on a combination of the findings from Jensen's inequality (Jensen, 1906) and Shannon's entropy (Shannon, 1948). The marginal topic distribution is the prevalence of the topic in the overall corpus and the larger the sphere is, the more important the topic is as a percentage of the overall corpus.

Finally, we estimate LDA models with and without TF-IDF[6]. We find at first that

[5]To construct Figure 1 we use the Mallet package in Python.

[6]The models without TF-IDF use a standard document-term matrix with unigrams and bigrams (see Table 2). The combination of LDA with the TF-IDF is tested to observe any possible increase in the precision of LDA in separating the topics.

Table 1: **Coherence and Perplexity scores for different numbers of Topics**

Number of Topic	**4**	**5**	**14**	**50**	**4**	**5**	**14**	**50**
Chunk size	*100*	*100*	*100*	*100*	*500*	*500*	*500*	*500*
Perplexity	-7.28	-7.27	-7.68	-9.01	-7.24	-7.22	-7.31	-7.79
Coherence score	0.42	0.39	0.43	0.45	0.40	0.39	0.44	0.37

The Chunk size is the number of documents trained by the model

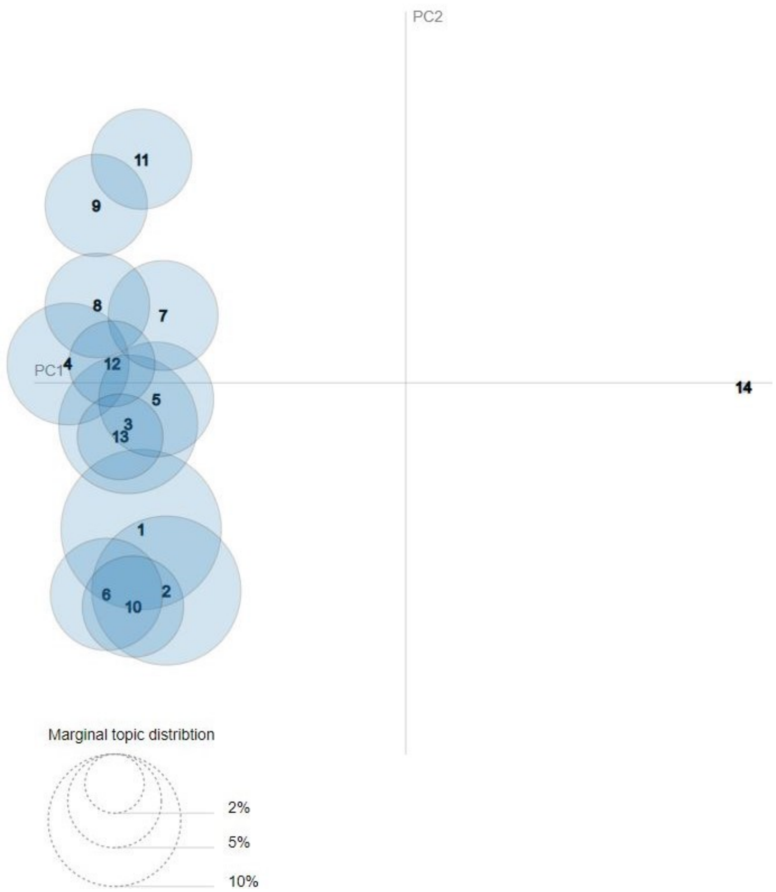

Figure 2: Intertopic distance map – number of topics is 14

Data source: ECB (2020)

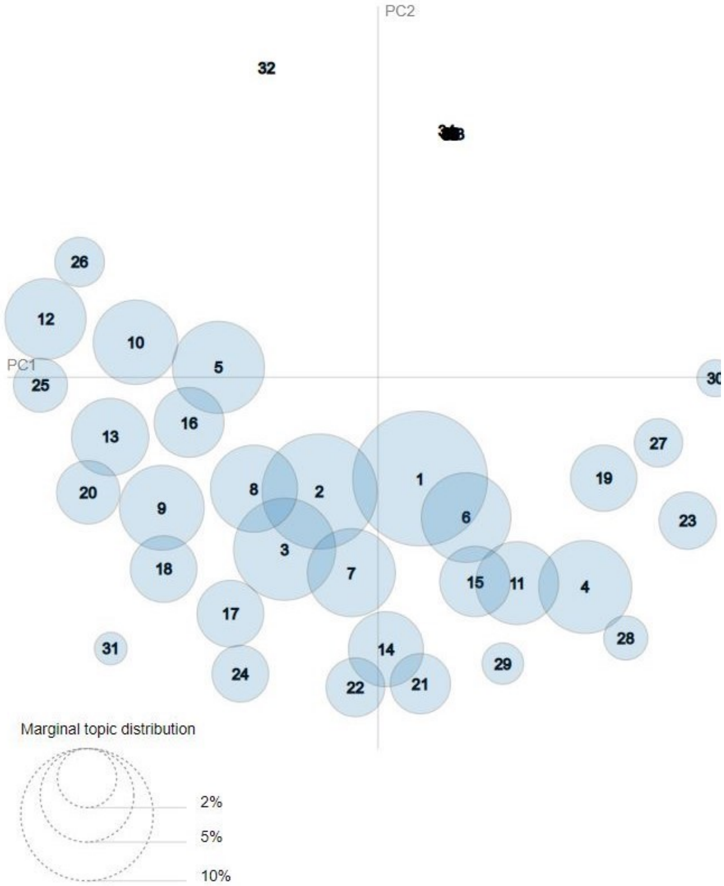

Figure 3: Intertopic distance map – number of topics is 50

Data source: ECB (2020)

there is no particular difference between using four or five topics, but when we observe the model with bigrams and five topics, it is evident that it performs better than the model with four topics for perplexity, and the two models have almost the same results for the coherence scores. Furthermore, the LDA models with only bigrams perform much better for coherence scores than those with only unigrams do. Finally, introducing TF-IDF slightly improves the perplexity score, but does not particularly affect the coherence scores. Interestingly, Blei et al. (2003) declare that LDA does not need TF-IDF.

However, Blei and Lafferty (2009) affirm that the combination of TF-IDF and LDA can be useful for reducing the vocabulary size and visualising the topics. This reduction is already visible in the previous analysis of bigrams and trigrams, where TF-IDF analysis highlighted unigrams that can be eliminated in the pre-processing step without relevant bigrams being lost. In addition, there is no need to use trigrams, as we observed. Given these results we employ an LDA model with bigrams and Gibbs Samplings, and we choose five as the number of topics[7]. Data visualisation of the topics can be seen in the Appendix (Figure A1).

Table 2: **LDA with TF-IDF and Bigrams - scores**

Model	**No TF-IDF**	**No TF-IDF**	**TF-IDF**	**TF-IDF**	**No TF-IDF**	**No TF-IDF**	**TF-IDF**	**TF-IDF**
Topics	*4*	*5*	*4*	*5*	*4*	*5*	*4*	*5*
Grams	*Unigrams*	*Unigrams*	*Unigrams*	*Unigrams*	*Bigrams*	*Bigrams*	*Bigrams*	*Bigrams*
Perplexity	-7.03	-7.00	-7.88	-7.92	-6.11	-7.26	-6.09	-7.38
Coherence	0.48	0.51	0.49	0.28	0.58	0.55	0.56	0.55

The results of the LDA method are used to create topic model indices with a similar approach to those of Thorsrud (2020) and Gabrielyan et al. (2019). Following their methods we select the 15 most frequent words from each topic extracted by LDA and compute the sum of the frequencies for each of these words for each topic in each daily document. In this way we construct daily indices for every topic. Next, we average the daily results by quarters to obtain quarterly indices[8]. Following Gabrielyan et al. (2019) the index can be described as:

$$I_{zt} = \sum_{d \in I_t} \sum_{w} F(d, w, z), \tag{3}$$

where I_{zt} is measure of frequency, or the frequency index of topic z at time t extracted with the LDA algorithm. $F(d,w,z)$ is the frequency of word w from topic z in document d. Each w corresponds to one of 15 most frequently occurring words in topic z. The

[7]More information on LDA can be found in Appendix I.

[8]Aggregating the speeches by quarter and directly creating quarterly indices leads to problems with the LDA in disentangling the topics, given the inferior number of documents available. Codes for the attempts at this procedure are available on request.

names of the topics are derived manually from the interpretation of the results and are later confirmed by observation of the results of the regressions, with particular focus on distinguishing the two topics related to the monetary policy of the ECB. We also take account of the LDA analysis performed by Hartmann and Smets (2018).

The names of the topics and the abbreviations for them are:

- Financial Stability and the Banking System (FSBS)
- Non-standard Monetary Policy (NMP)
- Canonical Monetary Policy (CMP)
- European Monetary Union and Growth (EMUG)
- Financial Integration and the Payment System (FIPS)

3.2 Data and Models

The indices are regressed by inflation, which is taken from the projections of the ECB and the quarterly one-year-ahead forecasts of the Survey of Professional Forecasters (SPF). The ECB forecasts are real-time and include the next calendar year projections for each quarter, so the projections of the first quarter of 2000 for the year 2001, the projections of the second quarter for the year 2001, and so on. Real GDP growth is taken from the ECB's website. We also introduce the control and financial variables used in Cour-Thimann and Jung (2020), such as the 3-quarter moving average *M3* annual growth at *t-2*, the Fed Funds target at *t-1*, the 3-quarter moving average credit growth for euro area residents as a replacement for the M3 variable at *t-2*, and the oil price at *t-1* as a further control variable[9]. This first model is partially similar to that of Cour-Thimann and Jung (2020), which we term the CJ model. As a robustness check, we replace our ECB and SFP forecasts with the ECB and SPF data used by Cour-Thimann and Jung (2020). A full description of the data and the sources is available in Table A1 of Appendix I. All data are normalised using z-score normalisation similar to that in Cour-Thimann and Jung (2020).

The formula of this model can be described as follows:

$$I_{zt} = \alpha + \beta_1 FINF_t + \beta_2 FGDP_t + \beta_3 FIN_{t-2} + \beta_4 FED_{t-1} + \beta_5 OIL_t + CRISIS|ZLB + e_t, \tag{4}$$

where $FINF_t$ is a group of variables that includes several forecast data for inflation such as the inflation forecasts of the ECB ($ECB\_F\_INF_t$), the inflation forecasts of the SPF ($SPF\_F\_INF_t$), and the inflation forecasts of the ECB with the data from Cour-Thimann and Jung (2020). $FGDP_t$ represents various forecast data for real GDP growth, such as the forecasts of the ECB ($ECB\_F\_GDP_t$), the forecasts of the SPF ($SPF\_F\_GDP_t$), and the forecasts of the ECB with the data from Cour-Thimann and Jung (2020). FIN_{t-2} are the financial variables, either $M3_{t-2}$ or credit growth, $CREDIT_{t-2}$. FED_{t-1} represents the FED funds target. OIL_t is the oil price and e_t is the error term. The lags are selected by considering when the information should be available to the ECB Board as in Cour-Thimann and Jung (2020), in our case using quarters. To check for the eventual differences between the full sample, the pre-crisis period, and the pre-lower bound period, we apply the method suggested by Cour-Thimann and Jung (2020) to account for the periods before 2008 and 2014. However, it is unclear if the results are due to the low level of observations, as this can cause some issues in the estimations. To tackle this issue, we create two dummies *CRISIS* and *ZLB*. For the *CRISIS* specifications the quarters from Q4 2000-Q3 2008 are set at 0 and the subsequent ones are 1. For ZLB specifications the dummy is equal to 0 in periods between Q4 2000-Q2 2014. The following quarters are equal to 1.

Finally, we estimate the model proposed by Hartmann and Smets (2018) which we term the HS model, replacing the short-term interest rate with our topic indices and including ECB projections with or without the SPF projections in the model. Moreover,

[9] We adapt the model to quarterly data. The differences in time arise from when the ECB gets new information on the independent variables.

the deviation of the projections from the inflation target of 1.81% estimated by Hartmann and Smets (2018) and the deviation of the GDP growth projection from potential output are reflected by dummy variables. The interactions of the deviations with the forecasts are also included in the model specifications, which is now as follows:

$$I_{zt} = \alpha + \beta_1 FECB_t + \beta_2 FSPF_t + \beta_3 DEV_t + \beta_4 FECB_t x DEV_t + CRISIS|ZLB + e_t, \quad (5)$$

where $FECB_t$ is a group of variables representing the ECB's forecasts for inflation ($ECB\_F\_INF_t$) and real GDP growth ($ECB\_F\_GDP_t$). $FSPF_t$ describes a group of variables composed of the SPF's forecasts for inflation ($SPF\_F\_INF_t$) and GDP growth ($SPF\_F\_GDP_t$). DEV_t indicates the two deviation dummies, which are DEV_INF_t and DEV_GDP_t.As mentioned above, we also include the dummies $CRISIS$ and ZLB.

We expect that the variables in the Cour-Thimann and Jung (2020) model like federal funds and credit growth are very relevant for topics like FSBS and FIPS. The forecast over GDP should be more important for the EMUG topic, and the inflation forecast should be relevant for the topics on monetary policies. Furthermore, we know that M3 growth was very important in the early days of the euro area as a tool providing information for the board of the ECB. We expect this to be highlighted by topics such as CMP. The oil price should be relevant for monetary policy as well, especially for NMP given the increased attention that this variable has received in recent years.

As for the HS model, the ECB forecast should, at least in general, be more relevant for the board of the ECB than the SPF forecasts are. In further analysis, we also aim to check for deviation from the inflation target and the output gap in the topics. In principle deviation from inflation should be more relevant for topics such as CMP and NMP. Deviation from the output gap could be relevant for EMUG and FSBS.

4 Empirical communication reaction functions of ECB

4.1 Financial Stability and the Banking System

We report the results of the two different models. We describe the full sample without the *CRISIS* and *ZLB* dummies of Cour-Thimann and Jung (2020) and the results of the Hartmann and Smets (2018) HS, model. The results for the CJ model with SPF forecasts and with the dummies are presented in Appendix I. The results with the reduced subsamples and the robustness check for the CJ data are available upon request.

As highlighted by Figure 3 and as expected, the topic of Financial Stability and the Banking System occurs increasingly in the ECB speeches during the period of the financial crisis of 2008-2009 and afterwards. These dynamics are related not only to the effects of the Great Recession but also to the creation of the European Banking Union, which assigned supervisory responsibilities to the ECB (Hartmann & Smets, 2018). The main results presented in Table 3 show that for CJ models the ECB's forecasts for real GDP growth and the federal funds rate have negative and highly significant effects on the frequency of the topic in speeches by the ECB, while the results for credit growth are positive and significant. Not surprisingly none of the variables related to monetary issues are significant in any of the four specifications of the model. The results are substantially the same when we replace the ECB forecasts with the SPF forecasts (see Table A2 in Appendix I). The only difference is for the inflation forecast, where there is negative significance when credit growth is included in the specifications. Replacing our data with those of Cour-Thimann and Jung (2020) causes a loss of significance for the federal funds. The results for the forecasts of GDP and credit growth are the same.

When the *CRISIS* dummy is introduced (Table A3 in the Appendix I), we can observe how the crisis affects the topic greatly. The dummy is extremely significant and it has positive effects on the frequency of the topic. It can also be noted that the inflation forecasts affect the frequency of the topic positively, and M3 growth becomes significant after the dummy is introduced. The forecast for real GDP is still negative and significant. The correlation could be arise from the effect of the Great Recession on the economies of the euro area, but this does not necessarily imply a causal relationship. However, the significance of the forecasts disappears when the credit growth variable replaces M3 growth in this framework. Introducing the *ZLB* dummy (Table A4 in Appendix I) does not affect the results of the baseline scenario.

The analysis of the HS model (Table 4) shows that the ECB forecasts have significant negative effects on real GDP in all specifications of the model. There are two other interesting findings besides this. Firstly, the deviation from potential output has a positive and strongly significant effect on the topic. Secondly, the crisis has a positive and significant level, even if at 10%, but it does not affect the significance of the forecasts of real GDP negatively.

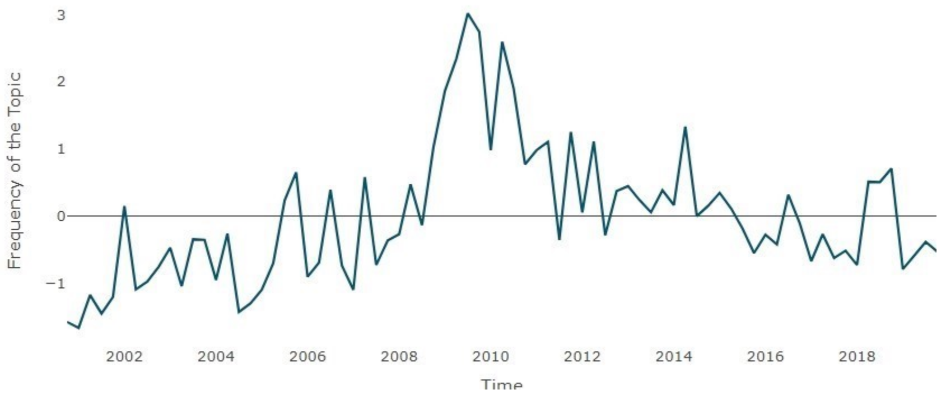

Figure 4: Topic - Financial Stability and the Banking System (FSBS), Q4 2000 - Q4 2019

Data source: ECB (2020) - normalised data

Table 3: **CJ model - Topic Financial Stability and the Banking System**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.12	0.02	0.13	0.02
	(0.11)	(0.11)	(0.11)	(0.11)
$ECB\_F\_GDP_t$	-0.49***	-0.34***	-0.50***	-0.35***
	(0.11)	(0.11)	(0.11)	(0.12)
$M3_{t-2}$	0.15		0.17	
	(0.10)		(0.11)	
FED_{t-1}	-0.38***	-0.62***	-0.36**	-0.62***
	(0.14)	(0.15)	(0.16)	(0.17)
$CREDIT_{t-2}$		0.44***		0.44***
		(0.12)		(0.12)
OIL_t			-0.05	0.00
			(0.16)	(0.14)
Intercept	-0.03	-0.04	-0.01	-0.04
	(0.09)	(0.08)	(0.11)	(0.10)
R^2	0.44	0.51	0.44	0.51
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **HS model - Topic Financial Stability and the Banking System**

	Mod 1	Mod 2	Mod 3	Mod 4	Mod5	Mod6
$ECB\_F\_INF_t$	-0.01	0.35**	0.00	0.12	0.18	-0.04
	(0.10)	(0.16)	(0.17)	(0.17)	(0.17)	(0.20)
$ECB\_F\_GDP_t$	-0.62***	-0.39**	-0.62***	-0.93***	-0.75***	-0.87***
	(0.10)	(0.19)	(0.10)	(0.17)	(0.19)	(0.17)
$SPF\_F\_INF_t$		-0.39***				
		(0.19)				
$SPF\_F\_GDP_t$		-0.34				
		(0.21)				
DEV_INF_t			-0.25	-0.36	-0.24	-0.49
			(0.53)	(0.52)	(0.52)	(0.52)
$ECB\_F\_INF\_ \times DEV\_INF_t$			0.13	0.14	0.16	0.32
			(0.39)	(0.38)	(0.38)	(0.40)
DEV_GDP_t				0.88***	0.53	0.97***
				(0.28)	(0.34)	(0.29)
$ECB\_F\_GDP \times DEV\_GDP_t$				0.24	0.3	0.2
				(0.21)	(0.21)	(0.21)
CRISIS					0.61*	
					(0.33)	
ZLB						-0.39
						(0.26)
Intercept	-0.00	-0.03	0.01	-0.72***	-0.84***	-0.67**
	(0.09)	(0.09)	(0.13)	(0.27)	(0.27)	(0.26)
R^2	0.38	0.46	0.39	0.44	0.47	0.46
N	77	77	77	76	76	76

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Non-standard Monetary Policy

Figure 5 illustrates the dynamics of the non-standard monetary policy topic index. We can observe stable movement in the index until 2014, after which it appears that the topic becomes more common. Non-standard monetary policies have become more relevant in recent years, since policies such as large-scale asset purchases and negative interest rates are employed (Hartmann & Smets, 2018). Table 5 shows the negative significant relationships at 1% between the topic and the forecasts of ECB for inflation, and at 5% with the oil price. The forecasts for GDP are only significant in the specification with M3 and the oil price. The results with the SPF forecasts (Table A5 in Appendix I) replicate the same results as for the ECB forecasts.

Introducing the Cour-Thimann and Jung (2020) data does not affect the general results significantly. The *CRISIS* dummy is highly significant in almost all specifications, and has a positive effect. The M3 growth is only significant at 10% in the first specification. Most importantly, the ECB forecasts remain significant and the forecasts for real GDP growth become positive and significant (Table A6 in Appendix I). Introducing ZLB (Table A7) has a major effect on the topics. The oil price remains significant and positive, M3 growth is weakly significant, and the forecasts of the ECB lose significance.

In the HS model (Table 6) we can still see the negative and significant results of the ECB inflation forecasts. However, when the SFP inflation forecasts are added, they become significant while the ECB forecasts become insignificant. Both dummies are significant and have positive effects on the topic of non-standard monetary policy. We can further observe that the interactions of the ECB's inflation forecasts and real GDP growth forecasts and their corresponding deviations, target and potential output, are significant. Interestingly, potential output remains relevant even after the introduction of the ZLB dummy.

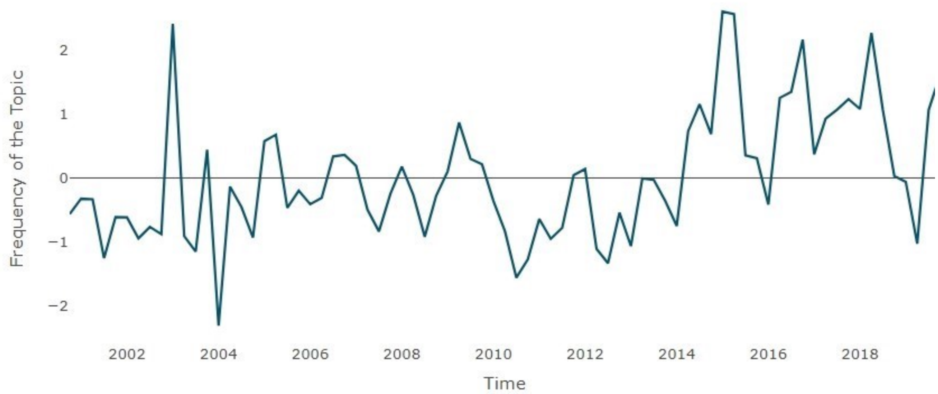

Figure 5: Topic - Non-standard Monetary Policy (NMP), Q4 2000 - Q4 2019

Data source: ECB (2020) - normalised data

Table 5: **CJ model - Topic Non-standard Monetary Policy**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.44***	-0.40***	-0.45***	-0.40***
	(0.14)	(0.14)	(0.14)	(0.14)
$ECB\_F\_GDP_t$	0.18	0.09	0.27**	0.19
	(0.13)	(0.14)	(0.13)	(0.14)
$M3_{t-2}$	0.06		-0.06	
	(0.12)		(0.13)	
FED_{t-1}	0.02	0.19	-0.15	-0.01
	(0.17)	(0.20)	(0.18)	(0.21)
$CREDIT_{t-2}$		-0.19		-0.22
		(0.16)		(0.15)
OIL_t			0.44**	0.42**
			(0.19)	(0.17)
Intercept	0.01	0.02	-0.15	-0.13
	(0.11)	(0.11)	(0.13)	(0.12)
R^2	0.15	0.17	0.21	0.24
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Canonical Monetary Policy

Figure 6 shows how interest in this topic, reflected by its frequency in the ECB speeches, declines after the crisis and stabilises at a new level afterwards. As Hartmann and Smets (2018) and Kaminskas et al. (2021) report, the main goal of the ECB when it was established was to assert credibility for its price stability strategy. Consequently importance was given to the M3 aggregate in this period (Hartmann & Smets, 2018).

Table 7 shows the results of the CJ models. The forecasts for real GDP by the ECB are significant at 5% and have a positive relationship with the canonical monetary policy topic, and so do M3 and credit growth. This changes when the ECB forecasts are replaced by the SFP forecasters (Table A8 in Appendix I). In this framework the forecast data lose significance. However, M3 remains statistical significant with a positive effect on the topic, and federal funds are also significant in the specifications with M3 growth[10]. With the Cour-Thimann and Jung (2020) data, the forecasts for GDP turn significant again, but only at 10%.

The introduction of the *CRISIS* dummy (Table A9) demonstrates how the dummy is extremely significant and how it neutralises the significance of all the variables. The framework is quite different when we replace the *CRISIS* dummy with the *ZLB* dummy (Table A10). The ECB forecast for real GDP is positive and statistically significant at

[10] Armelius et al. (2020) show the importance of the FED as a “leading spillover generator” among central banks through its communications. For Priola et al. (2021) this leading role increased after the Great Recession.

Table 6: **HS model - Topic Non-standard Monetary Policy**

	Mod 1	Mod 2	Mod 3	Mod 4	Mod5	Mod6
$ECB\_F\_INF_t$	-0.42***	0.05	-0.69***	-0.66***	-0.58***	-0.17
	(0.12)	(0.18)	(0.19)	(0.20)	(0.20)	(0.21)
$ECB\_F\_GDP_t$	0.18	0.12	0.22*	-0.06	0.2	-0.24
	(0.12)	(0.22)	(0.12)	(0.20)	(0.22)	(0.18)
$SPF\_F\_INF_t$		-0.55***				
		(0.16)				
$SPF\_F\_GDP_t$		0.01				
		(0.24)				
DEV_INF_t			-0.5	-0.63	-0.46	-0.23
			(0.61)	(0.61)	(0.60)	(0.56)
$ECB\_F\_INF \times DEV\_INF_t$			0.80*	0.91**	0.94**	0.37
			(0.44)	(0.45)	(0.44)	(0.43)
DEV_GDP_t				0.47	-0.04	0.2
				(0.34)	(0.39)	(0.31)
$ECB\_F\_GDP \times DEV\_GDP_t$				0.43*	0.51**	0.56**
				(0.25)	(0.25)	(0.23)
CRISIS					0.88**	
					(0.39)	
ZLB						1.17***
						(0.28)
Intercept	0.01	0.03	-0.13	-0.58*	-0.75**	-0.71**
	(0.11)	(0.10)	(0.14)	(0.31)	(0.31)	(0.28)
R^2	0.15	0.27	0.2	0.24	0.29	0.39
N	77	77	77	76	76	76

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1%, while the inflation forecast is significant at 10% when the credit is included in the specifications. ZLB is statistically significant at 1% and as expected, it has negative effects because it was absent in the periods when canonical monetary policy was more relevant.

The HS model sheds further light on the communication reaction function of the topic of canonical monetary policy. Most model specifications result in forecasts of real GDP being statistically significant and positive. As expected, the deviation of GDP from the output gap, and the interaction between the output gap and the forecast for GDP and the deviation in it are relevant. The latter is significant with both the dummies of the model.

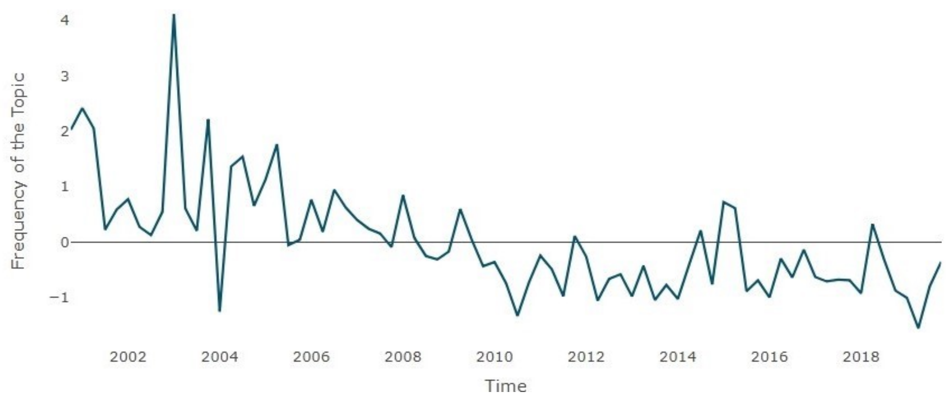

Figure 6: Topic - Canonical Monetary Policy (CMP), Q4 2000 - Q4 2019

Data source: ECB (2020) - normalised data

Table 7: **CJ model - Topic Canonical Monetary Policy**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.05	-0.02	0.05	-0.02
	(0.10)	(0.10)	(0.12)	(0.12)
$ECB\_F\_GDP_t$	0.27**	0.32**	0.24*	0.33**
	(0.12)	(0.13)	(0.12)	(0.14)
$M3_{t-2}$	0.26**		0.29**	
	(0.11)		(0.12)	
FED_{t-1}	0.19	0.13	0.23	0.11
	(0.16)	(0.18)	(0.17)	(0.20)
$CREDIT_{t-2}$		0.29**		0.28*
		(0.14)		(0.14)
OIL_t			-0.11	0.03
			(0.17)	(0.16)
Intercept	0.03	0.03	0.07	0.02
	(0.10)	(0.10)	(0.12)	(0.12)
R^2	0.31	0.29	0.31	0.29
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4 The European Monetary Union and Growth

Figure 7 illustrates how the topic of the launch of the euro cash by the European Monetary Union (EMU) was very prominent in the years before it happened, but it had lower frequency in ECB discussions in later years. However, the accession of new EU members with the 2004 enlargement kept the topic relatively visible until the Great Recession and the European sovereign debt crisis (Kaminskas et al., 2021). Structural and competitiveness issues were discussed before the financial crisis, as reported by Hartmann and Smets (2018).

The results of the regression presented in Table 9 show a positive and significant relationship between the topic and the forecasts for inflation and GDP, though the relationship with GDP is only significant at 10%. None of the other variables are relevant.

In the framework with the SPF forecasts (Table A11 in Appendix I), the relationship remains positive and statistically significant for inflation, though only at 10%. Introducing the Cour-Thimann and Jung (2020) data does not change the sign of the relationship or the significance of the inflation forecasts, but in some of the specifications the GDP forecasts are already positively and statistically significant at 5%. The *CRISIS* dummy is significant and when it is included, the M3 growth becomes negative and statistically significant at 10%. In the *ZLB* scenario (see Table A12) the GDP forecast is highly significant at either 5% or 1%. The *ZLB* dummy is negative and highly significant. Credit has a negative statistical significance at 5%.

In the HS models (Table 10), the forecasts of the ECB are significant and positively

Table 8: **HS model - Topic Canonical Monetary Policy**

	Mod 1	Mod 2	Mod 3	Mod 4	Mod5	Mod6
$ECB\_F\_INF_t$	0.21*	0.21	0.35*	0.2	0.05	-0.13
	(0.11)	(0.18)	(0.19)	(0.18)	(0.16)	(0.20)
$ECB\_F\_GDP_t$	0.31***	0.67***	0.29**	0.18	-0.25	0.31*
	(0.11)	(0.22)	(0.11)	(0.17)	(0.18)	(0.17)
$SPF\_F\_INF_t$		0.06				
		(0.17)				
$SPF\_F\_GDP_t$		-0.44*				
		(0.24)				
DEV_INF_t			-0.05	0.00	-0.29	-0.27
			(0.60)	(0.54)	(0.47)	(0.52)
$ECB\_F\_INF \times DEV\_INF_t$			-0.23	-0.24	-0.3	0.13
			(0.44)	(0.40)	(0.35)	(0.40)
DEV_GDP_t				-0.72**	0.13	-0.54*
				(0.30)	(0.31)	(0.29)
$ECB\_F\_GDP \times DEV\_GDP_t$				0.58**	0.45**	0.50**
				(0.22)	(0.21)	(0.21)
CRISIS					-1.48***	
					(0.31)	
ZLB						-0.79***
						(0.26)
Intercept	0.02	-0.03	0.11	0.56**	0.84**	0.65**
	(0.10)	(0.11)	(0.14)	(0.28)	(0.25)	(0.26)
R^2	0.19	0.23	0.2	0.35	0.52	0.43
N	77	77	77	76	76	76

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

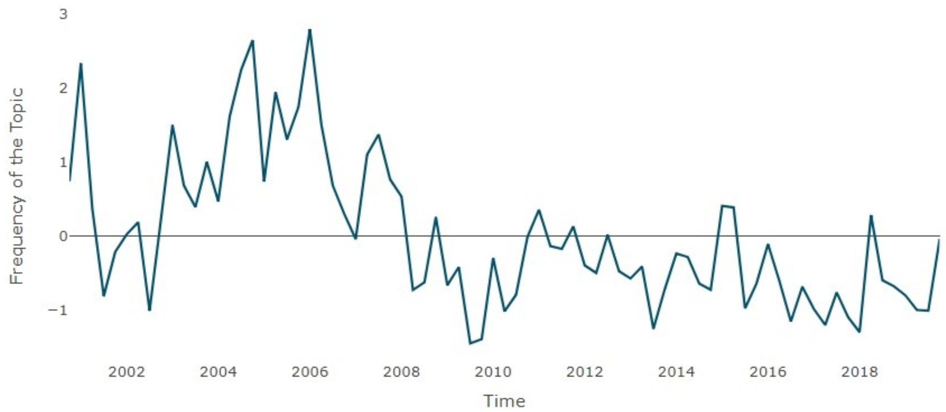

Figure 7: Topic - European Monetary Union and Growth (EMUG) (Q4 2000 - Q4 2019)

Data source: ECB (2020) - normalised data

related with the topic in the simpler specifications of the model. The SPF forecasts are not, however, significant. Deviations from the inflation target and potential output are significant, with the inflation target highly significant and potential output weakly significant and negative. The interactions between the inflation target and the inflation forecasts are negative and significant at either 5% or 10% depending on the specifications. Both the *CRISIS* and *ZLB* dummies are negative and significant. Introducing the *ZLB* dummy (Table A13) makes the GDP forecasts positive and significant, and does the same for deviation from the inflation target.

4.5 Financial Integration and the Payment System

Frequency analysis of the financial integration and payment system topic is presented in Figure 8. It can be seen that it was especially popular between 2004 and 2008, but its popularity as a topic starts to decline after 2010. It is notable that the peak of popularity was reached in 2006, when the ECB communicated a lot about payment and settlements (Hartmann & Smets, 2018). The shift from the TARGET system to the TARGET-2 system kept the ECB talking about the topic for some years more.

Table 11 illustrates the importance of the growth in federal funds and credit in terms of their statistical significance at 5% with a positive sign. The inflation forecasts are weakly significant when M3 growth is included in the specifications, and the SPF forecasts have similar results to the baseline scenario (Table A14). When we replace our data with those from Cour-Thimann and Jung (2020), the only variable to maintain its significance is federal funds. Introducing the *CRISIS* (Table A15) dummy, creates a significance of either 5% or 10% and a negative effect from ECB forecasts on real GDP. Federal funds is weakly positive and weakly significant at 10%. Inserting *ZLB* (Table A16) causes federal funds to become positive and significant again at 5%, while *ZLB* is negative and significant at 1%.

Table 9: **CJ model - Topic EMU and Growth**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.31**	0.31**	0.31**	0.31**
	(0.12)	(0.13)	(0.12)	(0.13)
$ECB\_F\_GDP_t$	0.22*	0.2	0.24*	0.23*
	(0.12)	(0.13)	(0.12)	(0.13)
$M3_{t-2}$	0.05		0.03	
	(0.11)		(0.12)	
FED_{t-1}	0.15	0.18	0.11	0.13
	(0.16)	(0.18)	(0.17)	(0.19)
$CREDIT_{t-2}$		-0.01		-0.02
		(0.14)		(0.14)
OIL_t			0.1	0.12
			0.17	0.16
Intercept	0.02	0.03	-0.01	-0.02
	(0.10)	(0.10)	(0.12)	(0.11)
R^2	0.32	0.32	0.32	0.32
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the HS framework (Table 12) there is some slight significance for the deviation from the potential output during the crisis and the interaction between forecast GDP and the deviation of potential output, as both are positive and significant at 5%. ECB forecasts of inflation are highly significant only in the simplest specification.

Table 10: **HS model - Topic EMU and Growth**

	Mod 1	Mod 2	Mod 3	Mod 4	Mod5	Mod6
$ECB\_F\_INF_t$	0.39 ***	0.31*	0.39**	0.28	0.16	-0.02
	(0.10)	(0.17)	(0.17)	(0.17)	(0.16)	(0.20)
$ECB\_F\_GDP_t$	0.26* *	0.43**	0.25**	0.26	-0.07	0.37**
	(0.10)	(0.21)	(0.10)	(0.17)	(0.19)	(0.17)
$SPF\_F\_INF_t$		0.12				
		(0.16)				
$SPF\_F\_GDP_t$		-0.19				
		(0.23)				
DEV_INF_t			1.31**	1.28**	1.06**	1.04**
			(0.54)	(0.53)	(0.50)	(0.52)
$ECB\_F\_INF \times DEV\_INF_t$			-0.82**	-0.72*	-0.76**	-0.39
			(0.40)	(0.39)	(0.39)	(0.40)
DEV_GDP_t				-0.51*	0.13	-0.35
				(0.29)	(0.33)	(0.29)
$ECB\_F\_GDP \times DEV\_GDP_t$				0.3	0.2	0.22
				(0.22)	(0.21)	(0.21)
CRISIS					-1.12***	
					(0.32)	
ZLB						-0.71***
						(0.26)
Intercept	0.01	-0.01	-0.03	0.31	0.53**	0.39
	(0.10)	(0.10)	(0.13)	(0.27)	(0.26)	(0.26)
R^2	0.3	0.32	0.36	0.41	0.5	0.47
N	77	77	77	76	76	76

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

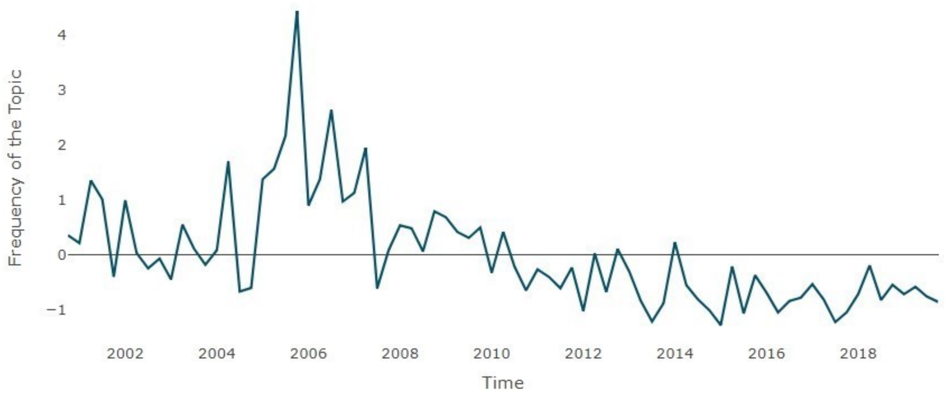

Figure 8: Topic - Financial Integration and Payment System (FIPS), Q4 2000 - Q4 2019

Data source: ECB (2020) - normalised data

Table 11: **CJ model - Topic Financial Integration and Payment System**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.24*	0.17	0.24*	0.17
	(0.12)	(0.12)	(0.12)	(0.12)
$ECB\_F\_GDP_t$	-0.11	-0.05	-0.1	-0.00
	(0.11)	(0.12)	(0.12)	(0.13)
$M3_{t-2}$	0.20*		0.18	
	(0.11)		(0.12)	
FED_{t-1}	0.38**	0.28	0.34**	0.2
	(0.15)	(0.17)	(0.17)	(0.19)
$CREDIT_{t-2}$		0.29**		0.28**
		(0.14)		(0.14)
OIL_t			0.09	0.16
			(0.17)	(0.15)
Intercept	0.04	0.03	0.00	-0.03
	(0.09)	(0.09)	(0.11)	(0.11)
R^2	0.36	0.37	0.36	0.38
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: **HS model - Topic Financial Integration and Payment System**

	Mod 1	Mod 2	Mod 3	Mod 4	Mod5	Mod6
$ECB\_F\_INF_t$	0.47***	0.3	0.32*	0.24	0.09	-0.18
	(0.11)	(0.18)	(0.19)	(0.19)	(0.17)	(0.21)
$ECB\_F\_GDP_t$	-0.01	0.27	0.00	-0.19	-0.63**	-0.03
	(0.11)	(0.22)	(0.11)	(0.19)	(0.19)	(0.18)
$SPF\_F\_INF_t$		0.27				
		(0.22)				
$SPF\_F\_GDP_t$		0.24				
		(0.16)				
DEV_INF_t			0.82	0.72	0.44	0.38
			(0.59)	(0.58)	(0.52)	(0.54)
$ECB\_F\_INF \times DEV\_INF_t$			-0.25	-0.11	-0.17	0.35
			(0.43)	(0.43)	(0.38)	(0.41)
DEV_GDP_t				-0.13	0.71**	0.1
				(0.32)	(0.33)	(0.30)
$ECB\_F\_GDP \times DEV\_GDP_t$				0.57**	0.44**	0.46**
				(0.24)	(0.21)	(0.22)
CRISIS					-1.47***	
					(0.34)	
ZLB						-1.00***
						(0.27)
Intercept	0.01	-0.03	-0.1	-0.11	0.18	0.00
	(0.10)	(0.11)	(0.14)	(0.30)	(0.27)	(0.27)
R^2	0.3	0.26	0.24	0.32	0.47	0.47
N	77	77	77	76	76	76

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Robustness Checks

Communications in central banking are generally bound to have a certain degree of autocorrelation because central banks show an internal coherence in their communication and forecasts [11]. For this reason, we perform the same regressions with other specifications. First we add one lag of the topics to the right side of the equations, as in Cour-Thimann and Jung (2020). Then we estimate the same regressions with four lags to account for any possible seasonality resulting because there are periods with fewer speeches, essentially the summer.

Finally, even though the total probabilities of our topics sum up to one in our time series, it is still possible that there is a certain degree of correlation between the topics [12]. To check this, we run an ordered probit model with Huber-White robust standard errors including one lag of the dependent variable, which is similar to the logic in Cour-Thimann and Jung (2020). To substitute the different level of the interest rate that the authors use in constructing their categorical dependent variable, we select the highest topic probability for each document at each point of time in our time series. This way we obtain a time index variable with a value between one and five.

4.6.1 Results of estimations with lags

The results[13] show important differences from the baseline scenario. The first lag is significant in all the models that include only one lag, but the picture is more complex in the models with four lags. The FSBS topic in the CJ model with one lag reduces the statistical relevance of the ECB forecasts for GDP to 10%. Credit growth and the Fed target are still very significant even in this scenario. In the HS model with one lag the ECB forecasts for GDP are still significant at 5% or 1% in most of the specifications, and the GDP deviation is significant at 1%. In the CJ model with four lags, the Fed targets only maintain their significance in half of the specifications. However, we can observe how only the first lag is statistically significant, while adding the other three lags does not particularly increase the R-squared of the estimations. In this sense the model with four lags is most probably over-specified. The HS model shows a similar pattern, where the ECB forecast for GDP is significant at 10% only in the last specification, while the GDP deviation is significant at 5%. In this model too the first lag appears to be the only significant one, and adding others does not increase the explanatory power of the model itself.

The CJ model for the non-standard monetary policy topic with the first lag shows that the inflation forecast is significant at 5%, while the oil price maintains its significance. A similar situation is found in the model with four lags, though there is a

[11] See Mirkov and Natvik (2016)

[12] Pearson correlation estimations suggest a strong correlation between the EMUG and CMP topics (0.71). We observe that these topics were quite important in the same timeframe. Other variables have correlations smaller than 0.5. Results are available upon request.

[13] Available upon request

decrease in significance for the ECB forecast for inflation. As with the previous topic however, adding new lags does not increase the R-squared of the estimations. In the HS model with one lag the ECB forecasts and the SPF forecast for inflation are still significant, while GDP deviation is significant at 5%. In the four lags version of the model the interaction between the ECB forecast for GDP and the deviation of GDP is significant at 10%. The only relevant lag is the first one and adding all the four lags only increases the R-squared by a few decimal points.

In the CJ model with one lag for canonical monetary policy, the significance of the ECB forecast for GDP and of M3 growth is reduced to 10%. Adding the four lags increases the R-squared of the OLS estimation considerably, but both the ECB forecasts and M3 growth lose significance and Fed targets becomes significant at 10%. Moreover, the third lag is more important than the first lag in terms of statistical significance. In the HS model with one lag, the ECB forecast for GDP is positive and statistically significant, as is the interaction between the ECB forecast for GDP and deviation of GDP. In the four lags version of the model, the ECB forecast for GDP is only significant at 5% in one specification. The interaction between the ECB forecast for GDP and deviation of GDP is significant at 10%. The third lag is again more relevant than the first lag.

In the CJ model for the European monetary union topic with one lag, no variable is significant. However, in the model with four lags the third lag is significant at 1% and Fed funds become statistically significant at between 5% and 10%. In the HS model with one lag the ECB forecast for inflation is significant at 5% only in the first specification. Inflation deviation and the interaction between the ECB forecast for inflation and inflation deviation are significant at 5%, but the interaction is only so in one specification. The interaction between the ECB forecast for GDP and the deviation of GDP is significant at 10%. The first lag is the most relevant even though the third lag is significant at 10% in some specifications. The HS model results in a similar picture, except that the interaction between the ECB forecast for inflation and inflation deviation decreases its significant from 5% to 10%.

The CJ model for the FIPS topic with one lag leads to only Fed funds being significant at 10% in only one specification. Adding the other three lags increases the R-squared from 0.45 to 0.55. The third lag is statistically significant, rather than the one lag version. The Fed funds are significant at 5% in the first specification and 10% in the second specification. However, in the HS model with one lag the ECB forecast for inflation is significant at 5% in the first specification and the interaction between the ECB forecast for GDP and deviation of GDP is significant at 10%. In the HS model with four lags both the first and the third lags are highly significant. The only variable that is significant at 10% is the interaction between the ECB forecast for GDP and deviation of GDP.

4.6.2 Results of estimations of the ordered probit model

The ordered probit model results are as expected in terms of the significance of the first lag of the dependent variable (Table A17). The ECB forecasts for inflation are highly negative with a significance at 1%. Credit growth is significant at 10% and only in one specification. Given that the topic of non-standard monetary policy is the only one where the ECB forecast for inflation is significant in the CJ model, these results confirm the importance of the inflation forecast in the ECB communication reaction function, and that extracting separate topics lets us analyse how each of these topics reacts to different variables. These results are similar to those of Cour-Thimann and Jung (2020).

5 Discussion of the results

Some of our results are in line with the findings in the literature. The findings of Hartmann and Smets (2018) for example at the variable level are that both the inflation forecasts and GDP forecasts are significant for determining the interest rate of the ECB. However, as we showed in this paper, the relevance depends on the topic under discussion. The significance and positive relationship with economic activity in the findings of Gerlach (2007) can be connected with the results of the CMP topic. The output is indeed important for the ECB (Carstensen, 2006) but only for some particular topics, not in general. However, the weakness of the results from the robustness checks means that conclusive results cannot be drawn.

With the findings for specific topics, Paloviita et al. (2020) similarly find two topics on monetary policy in ECB communication. We observe that financial stability is frequently mentioned in the speeches of the ECB, particularly in times of crisis. Although its relevance decreases in other years, it remains a fundamental topic of discussion for the ECB. Not surprisingly, financial variables like credit growth gain increasing importance at the ECB when it is necessary to intervene on issues related to financial stability and the banking system. Additionally, the relevance and significance of the federal funds for certain topics confirms that the ECB follows closely the communication and the actions of the Federal Reserve. This is also shown in a recent paper by Priola et al. (2020). As expected, the oil price is important when we observe the topic of non-standard monetary policy, and it is the only variable that remains significant, when the *ZLB* dummy is introduced. Overall, the *ZLB* dummy is extremely important for all the topics except the topic of financial stability. The *CRISIS* dummy meanwhile is highly significant in all the topics. Not surprisingly, the ECB generally prefers its own forecasts, as was also in Cour-Thimann and Jung (2020).

The results of the ordered probit model confirm the importance of the ECB forecast for its monetary policy. This is in line with the primary mandate of the ECB to keep inflation stable. Our paper, along with the topic analysis, confirms that monetary policy and price stability remain a central part of ECB communication, but we also observe how secondary objectives and financial stability have become more important since the Great Recession and the European sovereign debt crisis, even if they remain subordinated to the primary objective. The importance of non-standard monetary policies in recent years is a consequence of this hierarchy. It is worth noting that the deviation from the inflation target appears to be more relevant for non-standard monetary policy, which has become more important in recent years, than it is for canonical monetary policy. This is consistent with the mandate of the ECB, in broad terms, and its communications. Analysing topic indices in this environment makes clear the kind of information that the ECB is collecting to address both its primary and secondary objectives. This detailed analysis would not have been possible without using topics extracted by LDA process, since the effects of the different variables on different ECB topics would remain hidden in more comprehensive communication indices.

Conclusions

Our results show how the topic indices extracted from the speeches of the ECB can provide more detailed analysis than studies based on discrete dependent variables or simple tone indices can. These indices also give new insights into the communication reaction functions of central banks. We highlight in our findings how some results can be masked if the communication function is estimated in a single or, at most, a double dimension. Instead we make a positive contribution by extracting topic indices, which allows us to observe the impact of the significant variables on all the aspects of the communication reaction function.

However, some limitations remain. It is not always straightforward to interpret the signs of coefficients for instance. The positive relationship between credit growth and issues related to financial stability is clear, but explaining the sign of how the GDP forecasts relate to the topic of financial stability is not easy. To explain this relationship, more financial variables need to be introduced. Some are suggested in Rivolta (2018).

There is also a risk of misspecifications arising from the possible presence of non-linearity, and asymmetry of the loss function of the ECB (Cour-Thimann & Jung, 2020; Paloviita et al., 2020). Although our indices mean we do not have to work with ordered probit models as in Cour-Thimann and Jung (2020), we still estimate probit models in our robustness checks and find that identifying the most significant topic for each quarter can help in combining econometric methods and topic modelling and so tackle these issues to some extent.

Some statistical problems should be noted as well. Most of the indices do not pass the Dicky-Fuller test so there is a possible problem of non-stationarity. However, transforming the data by log-differencing could cause a loss of correlation between the indices and the independent variables, and it could also make the final results very complex to interpret.

It may finally be noted for the text mining aspects that using the LDA prototype method of Rieger et al. (2020) could improve the method of choosing the number of topics, but combining that with the literature on economic indices (Thorsrud, 2020; Gabrielyan et al., 2019) requires more research and deeper analysis.

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APPENDIX I

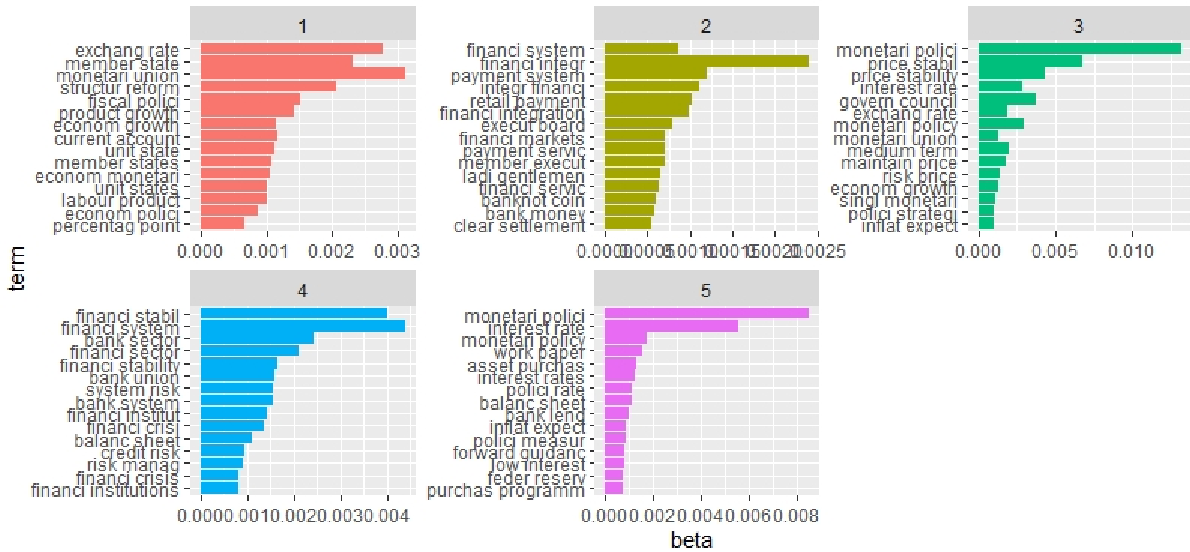

Figure A1: Topic indices - Top words

Data source: ECB (2020). Topic 1: European Monetary Union and Growth (EMUG); Topic 2: Financial Integration and Payment System (FIPS); Topic 3: Canonical monetary Policy (CMP); Topic 4: Financial Stability and Banking System (FSBS); Topic 5: Non-standard Monetary Policy (NMP)

Table A1: **Data and Sources**

Data	**Source and Data Description**
M3 data	ECB real-time database
Oil prices	ECB real-time database
Credit to euro arearesidents	ECB MFI statistics
Federal Funds rate	ALFRED data
ECB and SPF forecasts	Hand collected from ECB website
ECB and SPF forecasts by Cour-Thimann and Jung (2020)	Obtained from the authors
Output	European Commission data - used to calculate potential output growth

Table A2: **CJ model - Topic Financial Stability and Banking System with the Survey of Professional Forecasters**

	Mod 1	Mod 2	Mod 3	Mod 4
$SPF\_F\_INF_t$	-0.05	-0.19*	-0.04	-0.19*
	(0.11)	(0.11)	(0.11)	(0.11)
$SPF\_F\_GDP_t$	-0.50***	-0.31**	-0.50***	-0.30**
	(0.12)	(0.12)	(0.13)	(0.13)
$M3_{t-2}$	0.13		0.16	
	(0.10)		(0.11)	
FED_{t-1}	-0.27*	-0.57***	-0.24	-0.57***
	(0.15)	(0.15)	(0.16)	(0.17)
$CREDIT_{t-2}$		0.52***		0.52***
		(0.13)		(0.13)
OIL_t			-0.09	0.01
			(0.17)	(0.14)
Intercept	-0.08	-0.07	-0.05	-0.07
	(0.09)	(0.08)	(0.11)	(0.10)
R^2	0.42	0.52	0.42	0.52
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: **CJ model - Topic Financial Stability and the Banking System with the Dummy Crisis**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.31***	0.16	0.31***	0.16
	(0.12)	(0.10)	(0.12)	(0.10)
$ECB\_F\_GDP_t$	-0.31***	-0.16	-0.32***	-0.14
	(0.11)	(0.11)	(0.11)	(0.11)
$M3_{t-2}$	0.35***		0.37***	
	(0.10)		(0.11)	
FED_{t-1}	-0.25*	-0.51***	-0.22	-0.54***
	(0.14)	(0.14)	(0.15)	(0.15)
$CREDIT_{t-2}$		0.60***		0.60***
		(0.11)		(0.11)
OIL_t			-0.08	0.07
			(0.14)	(0.12)
CRISIS	1.17***	1.10***	1.18***	1.12***
	(0.31)	(0.26)	(0.31)	(0.26)
Intercept	-0.70***	-0.68***	-0.68***	-0.72***
	(0.19)	(0.17)	(0.20)	(0.18)
R^2	0.54	0.61	0.54	0.62
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: **CJ model - Topic Financial Stability and the Banking System with the Dummy ZLB**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.08	0.09	0.08	0.09
	(0.14)	(0.12)	(0.14)	(0.13)
$ECB\_F\_GDP_t$	-0.47***	-0.36***	-0.48***	-0.36***
	(0.11)	(0.11)	(0.12)	(0.12)
$M3_{t-2}$	0.14		0.15	
	(0.10)		(0.11)	
FED_{t-1}	-0.38***	-0.66***	-0.37**	-0.65***
	(0.14)	(0.16)	(0.16)	(0.17)
$CREDIT_{t-2}$		0.52***		0.52***
		(0.14)		(0.14)
OIL_t			-0.04	-0.02
			(0.16)	(0.14)
ZLB	-0.15	0.28	-0.14	0.28
	(0.25)	(0.26)	(0.26)	(0.27)
Intercept	0.02	-0.14	0.03	-0.13
	(0.12)	(0.12)	(0.13)	(0.13)
R^2	0.44	0.52	0.44	0.52
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: **CJ model - Topic Non-standard Monetary Policy with the Survey of Professional Forecasters**

	Mod 1	Mod 2	Mod 3	Mod 4
$SPF\_F\_INF_t$	-0.62***	-0.59***	-0.67***	-0.64***
	(0.12)	(0.13)	(0.11)	(0.12)
$SPF\_F\_GDP_t$	0.08	0.01	0.24*	0.21
	(0.13)	(0.14)	(0.13)	(0.14)
$M3_{t-2}$	0.08		-0.06	
	(0.11)		(0.11)	
FED_{t-1}	0.17	0.29	-0.04	0.00
	(0.16)	(0.18)	(0.16)	(0.19)
$CREDIT_{t-2}$		-0.1		-0.09
		(0.15)		(0.14)
OIL_t			0.57***	0.53***
			(0.17)	(0.16)
Intercept	0.05	0.05	-0.14	-0.13
	(0.10)	(0.10)	(0.11)	(0.11)
R^2	0.29	0.29	0.38	0.39
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: **CJ model - Topic Non-standard Monetary Policy with the Dummy Crisis**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.26*	-0.31**	-0.28*	-0.29**
	(0.15)	(0.15)	(0.14)	(0.14)
$ECB\_F\_GDP_t$	0.35**	0.21	0.43***	0.35**
	(0.14)	(0.15)	(0.14)	(0.15)
$M3_{t-2}$	0.25*		0.13	
	(0.13)		(0.14)	
FED_{t-1}	0.14	0.26	-0.02	0.05
	(0.17)	(0.20)	(0.18)	(0.20)
$CREDIT_{t-2}$		-0.09		-0.11
		(0.16)		(0.15)
OIL_t			0.41**	0.41***
			(0.18)	(0.17)
CRISIS	1.13**	0.7*	1.08***	0.83***
	(0.39)	(0.37)	(0.38)	(0.35)
Intercept	-0.64**	-0.38	-0.76***	-0.64**
	(0.25)	(0.24)	(0.25)	(0.24)
R^2	0.24	0.21	0.3	0.29
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: **CJ model - Topic Non-standard Monetary Policy with the Dummy ZLB**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.06	-0.09	-0.09	-0.11
	(0.14)	(0.14)	(0.14)	(0.14)
$ECB\_F\_GDP_t$	0.01	0.03	0.08	0.12
	(0.12)	(0.13)	(0.13)	(0.13)
$M3_{t-2}$	0.19*		0.11	
	(0.11)		(0.12)	
FED_{t-1}	0.03	-0.01	-0.08	-0.15
	(0.15)	(0.18)	(0.16)	(0.19)
$CREDIT_{t-2}$		0.2		0.15
		(0.16)		(0.16)
OIL_t			0.28*	0.33**
			(0.17)	(0.15)
ZLB	1.30***	1.38***	1.21***	1.29***
	(0.26)	(0.30)	(0.27)	(0.30)
Intercept	-0.43**	-0.46**	-0.50***	-0.55***
	(0.13)	(0.14)	(0.14)	(0.15)
R^2	0.37	0.36	0.39	0.39
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: **CJ model - Topic Canonical Monetary Policy with the Survey of Professional Forecasters**

	Mod 1	Mod 2	Mod 3	Mod 4
$SPF\_F\_INF_t$	-0.02	-0.09	-0.01	-0.09
	(0.12)	(0.13)	(0.12)	(0.13)
$SPF\_F\_GDP_t$	0.14	0.17	0.09	0.17
	(0.13)	(0.14)	(0.14)	(0.16)
$M3_{t-2}$	0.24**		0.28**	
	(0.11)		(0.12)	
FED_{t-1}	0.33**	0.29	0.39**	0.29
	(0.16)	(0.19)	(0.18)	(0.21)
$CREDIT_{t-2}$		0.25		0.25
		(0.16)		(0.16)
OIL_t			-0.16	-0.00
			(0.18)	(0.17)
Intercept	0.06	0.06	0.11	0.06
	(0.10)	(0.10)	(0.12)	(0.12)
R^2	0.26	0.25	0.27	0.25
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: **CJ model - Topic Canonical Monetary Policy with the Dummy Crisis**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.17	-0.19	-0.17	-0.19
	(0.12)	(0.12)	(0.12)	(0.12)
$ECB\_F\_GDP_t$	0.05	0.08	0.04	0.07
	(0.12)	(0.13)	(0.12)	(0.13)
$M3_{t-2}$	0.02		0.04	
	(0.11)		(0.12)	
FED_{t-1}	0.03	-0.01	0.06	0.01
	(0.15)	(0.16)	(0.16)	(0.18)
$CREDIT_{t-2}$		0.09		0.09
		(0.13)		(0.13)
OIL_t			-0.07	-0.05
			(0.16)	(0.14)
CRISIS	-1.4***	-1.38***	-1.4***	-1.39***
	(0.33)	(0.30)	(0.33)	(0.30)
Intercept	0.84**	0.82***	0.87**	0.85**
	(0.21)	(0.19)	(0.21)	(0.21)
R^2	0.45	0.45	0.45	0.45
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: **CJ model - Topic Canonical Monetary Policy with the Dummy ZLB**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.2	-0.24*	-0.2	-0.24*
	(0.14)	(0.14)	(0.14)	(0.14)
$ECB\_F\_GDP_t$	0.38***	0.36***	0.38***	0.39***
	(0.11)	(0.12)	(0.12)	(0.13)
$M3_{t-2}$	0.17		0.17	
	(0.10)		(0.12)	
FED_{t-1}	0.19	0.27	0.18	0.22
	(0.15)	(0.17)	(0.16)	(0.19)
$CREDIT_{t-2}$		0.01		-0.01
		(0.16)		(0.15)
OIL_t			0.01	0.11
			(0.16)	(0.15)
ZLB	-0.88***	-0.97***	-0.88***	-1.00***
	(0.25)	(0.29)	(0.26)	(0.30)
Intercept	0.33***	0.37***	0.33**	0.34**
	(0.12)	(0.14)	(0.13)	(0.14)
R^2	0.41	0.38	0.41	0.39
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: **CJ model - Topic EMU and Growth with the Survey of Professional Forecasters**

	Mod 1	Mod 2	Mod 3	Mod 4
$SPF\_F\_INF_t$	0.21*	0.23*	0.21*	0.22
	(0.12)	(0.13)	(0.12)	(0.13)
$SPF\_F\_GDP_t$	0.2	0.17	0.22	0.2
	(0.13)	(0.14)	(0.14)	(0.16)
$M3_{t-2}$	0.04		0.02	
	(0.11)		(0.12)	
FED_{t-1}	0.24	0.29	0.21	0.24
	(0.16)	(0.18)	(0.18)	(0.21)
$CREDIT_{t-2}$		-0.04		-0.04
		(0.15)		(0.15)
OIL_t			0.07	0.08
			(0.18)	(0.17)
R^2	0.28	0.28	0.28	0.28
Intercept	0.05	0.05	0.02	0.02
	(0.10)	(0.10)	(0.12)	(0.12)
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: **CJ model - Topic EMU and Growth with the Dummy Crisis**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.06	0.14	0.06	0.14
	(0.12)	(0.12)	(0.12)	(0.12)
$ECB\_F\_GDP_t$	-0.01	-0.03	0.01	-0.02
	(0.11)	(0.12)	(0.12)	(0.13)
$M3_{t-2}$	-0.2*		-0.25*	
	(0.11)		(0.12)	
FED_{t-1}	-0.02	0.04	-0.08	0.03
	(0.14)	(0.16)	(0.15)	(0.17)
$CREDIT_{t-2}$		-0.21		-0.21
		(0.13)		(0.13)
OIL_t			0.14	0.03
			(0.13)	(0.13)
CRISIS	-1.52***	-1.38***	-1.54***	-1.37***
	(0.32)	(0.30)	(0.32)	(0.30)
Intercept	0.90**	0.82***	0.86**	0.81**
	(0.20)	(0.19)	(0.21)	(0.21)
R^2	0.48	0.48	0.49	0.48
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: **CJ model - Topic EMU and Growth with the Dummy ZLB**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.06	0.04	0.03	0.03
	(0.14)	(0.13)	(0.14)	(0.13)
$ECB\_F\_GDP_t$	0.33***	0.25**	0.39***	0.31**
	(0.11)	(0.12)	(0.12)	(0.12)
$M3_{t-2}$	-0.03		-0.1	
	(0.10)		(0.12)	
FED_{t-1}	0.14	0.35**	0.06	0.26
	(0.15)	(0.17)	(0.16)	(0.18)
$CREDIT_{t-2}$		-0.34**		-0.37**
		(0.15)		(0.15)
OIL_t			0.22	0.21
			(0.16)	(0.14)
ZLB	-0.86***	-1.18***	-0.93***	-1.24***
	(0.25)	(0.28)	(0.26)	(0.28)
Intercept	0.31**	0.44***	0.26*	0.38***
	(0.12)	(0.13)	(0.13)	(0.14)
R^2	0.42	0.45	0.43	0.47
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A14: **CJ model - Topic Financial Integration and the Payment System with the Survey of Professional Forecasters**

	Mod 1	Mod 2	Mod 3	Mod 4
$SPF\_F\_INF_t$	0.20*	0.13	0.20*	0.12
	(0.11)	(0.12)	(0.12)	(0.12)
$SPF\_F\_GDP_t$	-0.14	-0.08	-0.13	-0.04
	(0.12)	(0.13)	(0.13)	(0.15)
$M3_{t-2}$	0.18*		0.17	
	(0.11)		(0.12)	
FED_{t-1}	0.42***	0.34*	0.42**	0.28
	(0.15)	(0.17)	(0.17)	(0.19)
$CREDIT_{t-2}$		0.26*		0.26*
		(0.14)		(0.14)
OIL_t			0.02	0.13
			(0.17)	(0.16)
Intercept	0.02	0.02	0.01	-0.02
	(0.09)	(0.09)	(0.11)	(0.11)
R^2	0.36	0.36	0.36	0.37
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A15: **CJ model - Topic Financial Integration and the Payment System with Dummy Crisis**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.08	0.06	0.08	0.06
	(0.13)	(0.12)	(0.13)	(0.12)
$ECB\_F\_GDP_t$	-0.26**	-0.20	-0.24*	-0.17
	(0.12)	(0.13)	(0.13)	(0.14)
$M3_{t-2}$	0.04		0.01	
	(0.12)		(0.13)	
FED_{t-1}	0.27*	0.19	0.22	0.14
	(0.15)	(0.17)	(0.16)	(0.18)
$CREDIT_{t-2}$		0.16		0.15
		(0.14)		(0.14)
OIL_t			0.11	0.11
			(0.16)	(0.15)
CRISIS	-0.97***	-0.91***	-0.99***	-0.88***
	(0.34)	(0.31)	(0.34)	(0.31)
Intercept	0.60***	0.56***	0.56**	0.50**
	(0.21)	(0.20)	(0.22)	(0.21)
R^2	0.43	0.44	0.43	0.44
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A16: **CJ model - Topic Financial Integration and the Payment System with the Dummy ZLB**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	0.01	-0.01	-0.02	-0.03
	(0.13)	(0.14)	(0.14)	(0.13)
$ECB\_F\_GDP_t$	-0.01	-0.01	0.04	0.05
	(0.11)	(0.12)	(0.12)	(0.12)
$M3_{t-2}$	0.12		0.06	
	(0.10)		(0.11)	
FED_{t-1}	0.37**	0.40**	0.30*	0.29
	(0.14)	(0.17)	(0.16)	(0.18)
$CREDIT_{t-2}$		0.06		0.02
		(0.15)		(0.15)
OIL_t			0.2	0.23
			(0.16)	(0.15)
ZLB	-0.80***	-0.81***	-0.86***	-0.88***
	(0.25)	(0.29)	(0.25)	(0.29)
Intercept	0.30**	0.31**	0.25*	0.25*
	(0.12)	(0.13)	(0.13)	(0.14)
R^2	0.44	0.43	0.45	0.45
N	77	77	77	77

Standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A17: **CJ ordered probit model with one lag**

	Mod 1	Mod 2	Mod 3	Mod 4
$ECB\_F\_INF_t$	-0.94***	-0.87***	-0.94***	-0.87***
	(0.26)	(0.24)	(0.26)	(0.24)
$ECB\_F\_GDP_t$	0.13	0.06	0.13	0.01
	(0.20)	(0.20)	(0.20)	(0.22)
$M3_{t-2}$	-0.38		-0.38	
	(0.24)		(0.27)	
FED_{t-1}	-0.01	0.14	-0.00	0.21
	(0.24)	(0.27)	(0.25)	(0.27)
$CREDIT_{t-2}$		-0.46*		-0.44
		(0.28)		(0.27)
OIL_t			-0.01	-0.19
			(0.32)	(0.28)
$Topics_{t-1}$	0.77***	0.78***	0.77***	0.77***
	(0.23)	(0.23)	(0.23)	(0.23)
$Pseudo-R^2$	0.51	0.51	0.51	0.51
N	77	77	77	77

Robust standard errors are reported in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Supplementary explanations of LDA

Latent Dirichlet Allocation is an approach used in topic modelling that is based on the probabilistic vectors of words, which signal the importance of those words for the text corpus. LDA allows the topic probability distribution to be derived by assigning probabilities to each word and document. Assigning words and documents to multiple topics also has advantage of semantic flexibility, since the word 'rate' for example can relate to the topics of both inflation and unemployment. Thorsrud (2020) notes that LDA shares many features with Gaussian factor models, with the difference being that the factors here are topics and that they are fed through a multinomial likelihood at the observation.

In LDA each document is given a probability distribution and a topic assignment is made for each word in each document. The joint distribution of topic mixture θ, which is a set of N words w is given by:

$$p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha) \times \prod_{n=1}^{N} p(z_n|\theta) \times p(w_n|z_n, \beta) \tag{1}$$

where parameters α and β are vectors with components greater than zero. In addition, the topic distribution of each document is distributed as:

$\theta \sim Dirichlet(\alpha)$

and word distribution is modelled by

$z_n \sim Dirichlet(\beta)$

and

$N \sim Poisson(\xi)$

The goal of the LDA model is therefore to estimate θ and z in order to find which words are important for which topic and which topics are important for a given document. The higher that α and β are, the more likely it is that each document will contain a mixture of most topics rather than a single topic, and the more likely it is that each topic will contain a mixture of most of the words and not just single words. More technical and through specifications of the LDA model and topic modelling in general are provided in Blei et al. (2003) and Griffiths and Steyvers (2004).

Our LDA uses the Gibbs sampling method, which is an algorithmic method for successively sampling conditional distributions of variables and allows the topic representations within documents to be improved, together with the word distributions of all the topics. It may be noted that different model iterations and different parameters of α and β in (4) result in different document clustering. However, the goal is to find unknown patterns so there is no perfect value for the number of topics and the solutions will most likely be different for different values. Hence the choice of the number of topics to be extracted from the corpus can be based on knowledge of the domain and the literature on it. As such, we classified five different topics. Additional tests and analysis confirm the topic structure uncovered by LDA.

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