STRATEGICA International Conference, 11th edition, October 26-27 2023, Bucharest

DECISION MANAGEMENT IN THE EUROPEAN CENTRAL BANK. LDA MODELLING FOR COVID-19 AND THE UKRAINE WAR

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doi: 10.25019/STR/2023.002

Abstract
The European Central Bank tries to make its decision-making process transparent and open to the general public. As part of the initiative, they offer all of the speeches the board members gave at the executive meetings. The goal of this paper is to use modern statistical techniques developed in the area of natural language processing to gain insight into the decisions and directions that the ECB made in the last years during multiple crises, namely the stopping of the economy during the COVID-19 period and the problems for the European economy during the war in Ukraine. To do this, we are using Latent Dirichlet Allocation (LDA), finding out the main topics of discussion and identifying the main issues and directions of the ECB. Moreover, we will also generate a dynamic topic model of the text corpus to provide a richer set of information about the positions taken in the ECB leadership during COVID-19 and the war in Ukraine. The main economic problems, such as inflation or the spike of interest rates, can be found by topic analysis of the ECB speeches and other directions, such as the push for a digital currency in the EU or the push for a greener economy, that tend to change during big crises, and the way their frequency changes in the speeches tend to be linked with the important outside events. Our paper combines modern statistical techniques and institutional transparency data showing how these can be used to understand the European economy better.

Keywords
european central bank; sentiment analysis; latent dirichlet allocation; eurozone; speech data.

Introduction

Natural Language Processing techniques and Topic Models for textual data have existed for many years. However, we have seen a significant rise in these techniques since the large-scale adoption of Large Language Models. The idea of linking quantifiable textual data, like investors' sentiment, news sentiment, or Topic Analysis of the main trends in time as found in big corpuses of textual data, has also been fruitfully researched in the past by different researchers.

The European Central Bank, the leading actor regarding financial decisions made in the Euro Zone, has publicly published the speeches made by its Governing Council ever since its creation. Many researchers have studied this data and even managed to link it predictively to aspects of the real economy.

Considering this, our paper proposes using Latent Dirichlet Allocation (LDA) to find out what the main topics of discussion were in the Governing Council of the ECB. LDA models are probabilistic topic models, which can be estimated using a corpus of text data. We consider having a quick, quantifiable way of finding out the main topics of discussion in the ECB as being extremely important since, as will be described in the literature review, there have been authors that managed to correlate the EU economies growth, as described by their based on this speech data. Moreover, instead of looking statically at the topics, we are going to employ techniques to model the topics dynamically through time and see the evolution of the main words discussed and also of the topics themselves to enrich the set of information gained about the European economy through the COVID-19 and the start of the war in Ukraine.

Literature review

The idea behind analyzing the speeches done by the European Central Bank's (ECB) board members or presidents is not new in the literature. There have been many attempts to use the speech data provided by the ECB. Bennani and Neuenkirch (2017) analyze whether the speeches from the ECB are mainly effects of the economic conditions of certain periods, thus treating them as dependent variables. Other authors, such as Warin and Sanger (2020) and Anastasiou and Katsafados (2023), use the speeches as an independent variable, employing NLP techniques to check whether there are economic outcomes that derive from the positions taken by the ECB's governing body. Moreover, there are significant statistical correlations between the ECB's positions from a sentiment analysis perspective and different countries' national economies, as quantified by their stock market indices (Anand et al., 2022).

Considering this, we believe the analysis of the main topics discussed by the ECB's executive board during the last few years is fundamental since we can already see a significant correlation between the positions taken and the European economy. To do this, we will employ the use of Latent Dirichlet Allocation to find out the main areas of discussion for the periods of COVID-19 and the war in Ukraine. Latent Dirichlet Allocation is a *"generative probabilistic model of a text corpus"* (Blei et al., 2001). The model aims to find the main topics in a document or a set of documents, which is why the authors also suggest looking at this technique from a dimensionality reduction perspective.

Perplexity and coherence measures have been used in the literature to evaluate the performance of topic models such as LDA for a long time, as described by (Gurdiel et al., 2021). They can help us achieve an optimal number of topics to look for in text documents and evaluate the generalization performance of our topic model, namely LDA.

Measuring the sentiment polarity in text data to predict certain outcomes of market conditions has already been studied in the economics literature. It has even been used to study ECB speech data (Anastasiou & Katsafados, 2023). However, we propose using the sentiment polarity to analyze the effect of the COVID-19 pandemic and the war in Ukraine on the positions taken by the ECB and only get the overall state of the market as seen by the ECB.

In the machine learning literature, grid search techniques are employed to find the optimal hyperparameters to estimate probabilistic models. This technique can be seen in a multitude of papers, such as Belete and Huchaiah (2022) and Jiang and Xu (2022), and refers to the estimation of multiple models to find out the best-performing parameters given specific testing measures, such as the ones described above, namely coherence and perplexity.

Dynamic Topic Modelling is an extension of LDA that helps analyze the evolution of specific topics over time (Blei & Lafferty, 2006). This is especially important since a statical analysis of a given corpus of texts will never provide the same amount of information as seeing how this corpus evolved in time.

Methodology

As stated in the previous section, the ECB's positions seem to have some effect on the European economy or at least provide valuable insights into its inner functioning mechanisms. Taking this into consideration, we consider the answer to the questions: " What were the main topics of discussion in the ECB governing council during the periods of COVID-19 and the start of the war in Ukraine?" and " How have these positions changed and continued to change during these two periods" to have solid importance for investors, government actors, researchers, and the general population.

The dataset consists of 2643 total speeches. However, for comparison purposes, we will use the full dataset for descriptive purposes only to illustrate the general discussion themes in the ECB for all the recorded history. For our analysis, we will consider a subset of 294 speeches from January 2020 onwards. The dataset will be further split into two subsets, one ranging from January 2020 (start of COVID-19 actions worldwide according to the World Health Organization Timeline (WHO, n.d.) until 24 February 2022 (start of the war in Ukraine). The second subset will consist of the speeches from 24 February 2023 until the present day.

The analysis will be split into three subsections. The first is a descriptive subsection in which we aim to gather more insight into the studied data by employing techniques such as word clouds in Python better to visualize the raw data of the studied periods. The second will estimate an optimal LDA model for each of the given subsets to see the main topics of discussion in the ECB governing committee during the studied period. To have the optimal model, we will conduct a grid search based on both coherence and perplexity scores. Apart from the static LDA model, a dynamic topic modeling analysis will be performed to see the evolution of the topics over time (Blei & Lafferty, 2006). This is the most important part of any LDA analysis, as it tends to enrich the conclusions you can draw, especially if you consider different events that occurred in the economic environment during the studied period.

The mathematical details of LDA (Blei et al., 2001) and DTM (Blei & Lafferty, 2006) are beyond the scope of this paper and can be found in the original papers. In this paper, we will use the implementations in Python provided by the following libraries: *Gensim* for LDA and, of course, for data pre-processing, selection, and visualization. We will use the following helper libraries: *numpy, pandas, WordCloud, matplotlib, nltk, pyLDAvis.*

Results and discussion

To start with the analysis, it is better to understand the datasets under study by looking at the word clouds for each. Below, we can see the word clouds for the subset of speeches taken during the COVID-19 period.

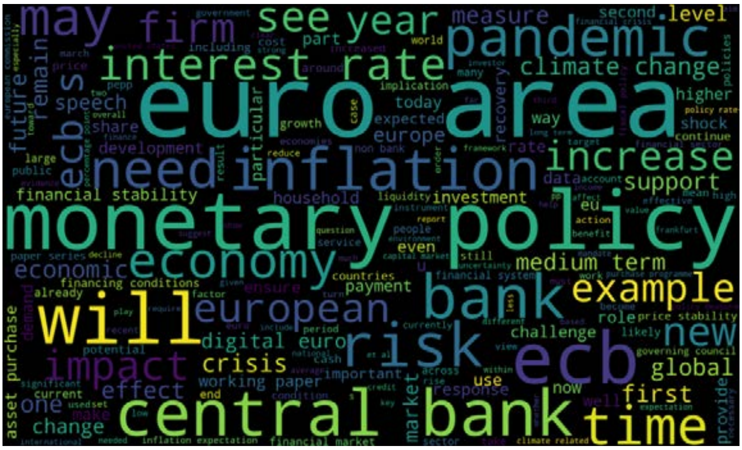

Figure 1. Word Cloud for the COVID-19 subset of data
(Source: Authors' own research results)

It seems immediately apparent what the main themes of study in the COVID-19 subset are. First, inflation is a significant consideration during COVID-19, with many smaller discussions on the financing conditions, support for the member countries, and keeping a certain price stability.

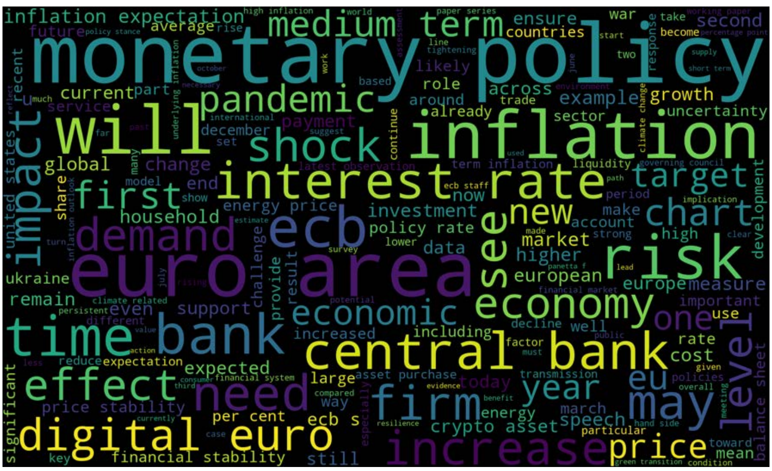

Figure 2. Word Cloud for the war in Ukraine subset
(Source: Authors' own research results)

In the second period of the analysis, we can already see words like shock, energy, Ukraine, and war appearing in the speeches of the ECB. As we already know from the current developments, the inflationary period that began with the COVID-19 pandemic was continued and aggravated by the war in Ukraine. Apart from these, there seem to be common areas on both periods, such as monetary policy and the digital euro, a discussion that isn't clear on how and when it will happen.

LDA Modelling

After conducting a grid search analysis training over 500 LDA models, we arrived at an optimal one, based on the coherence and perplexity scores, created with the full dataset from both subsets of data, that splits the text corpus into seven topics. The topic interpretation was done with the help of ChatGPT, based on the most frequently used terms within the issues. The topics, along with some of the most frequent keywords, as generated in the corpus, are:

Topic 1: Economic Impact of the Pandemic and War
Topic 2: Financial Markets, Policy Response, and Geopolitical Risk
Topic 3: Inflation, Economic Trends, and Geopolitical Influences
Topic 4: Financial Sector Stability and Risk Management
Topic 5: Digital Payments, Financial Innovation, and Geopolitical Factors
Topic 6: Green Economy, Climate Change, and Geopolitical Considerations
Topic 7: Climate Risks, Banking Supervision, and Geopolitical Challenges

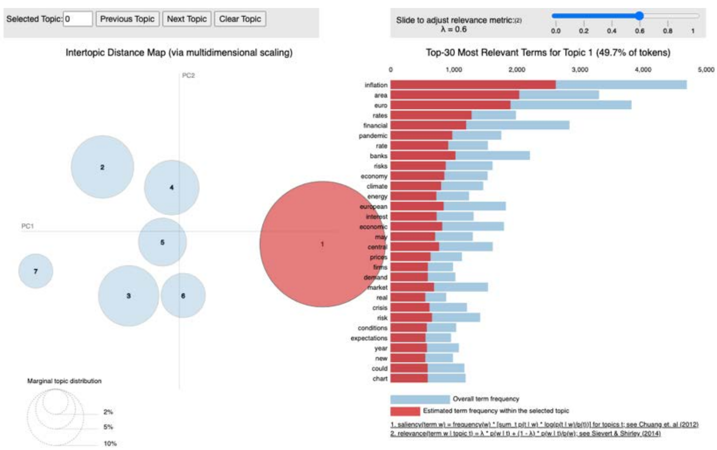

Figure 3. Visualization of the most salient terms in the generated topics (Source: Authors' own research results)

Instead of taking into account the simple term probability of being in a different topic in LDA, the authors of the pyLDAviz library define a new measure, saliency, as follows (Chuang et al., 2012):

$$distinctiveness(w) = \sum_{T} P(T|w) \log \frac{P(T|w)}{P(T)}$$
$$saliency(w) = P(w) \times distinctiveness(w)$$

Where ***P(T|w)*** *is the probability that observed word w was generated by latent topic T, and* ***P(T)*** *is the probability that any randomly-selected word* ***w*** *was generated by topic T."* This gives us a better measure for visualizing different topics, as a lot of the words can appear in multiple topics.

As we can see in the visualization above, topic 1 already contains half of the dataset, which is more or less obvious, because it describes most of the economic issues since the pandemic started. It includes terms such as inflation, euro area, risk, demand, market, economy, prices, etc., making it one of the most important topics to include in our Topic Modelling Analysis.

We can also see from Figure 3 that the other 50% of the dataset is split between 6 different topics, each with specific debate themes. For example, topic 6 describes the problems that have arisen in the green economy and climate change from the beginning of the war, while topic 5 is related to the digitalization of the economy. All the other topics are different subsets of these.

Dynamic Topic Modelling

As already described in the Literature Review and methodology, dynamic topic models are essentially models that describe the evolution of certain topics through time. We will consider Topics 1, 5, and 6 for our analysis, as they contain the most important subjects debated in the datasets under consideration.

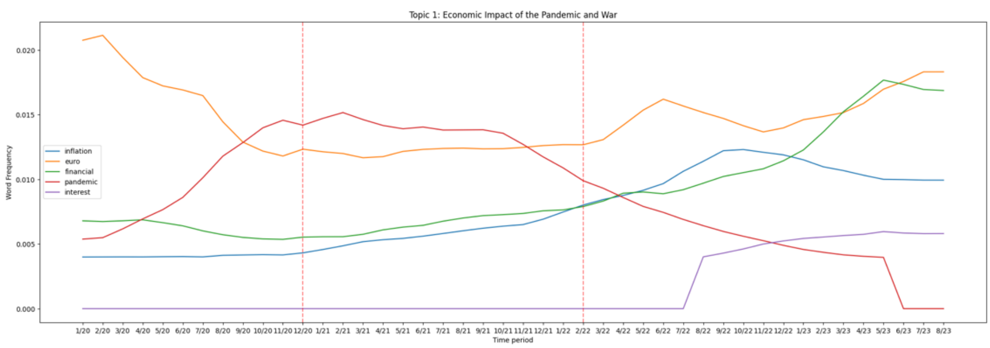

Figure 4. Topic 1 Dynamic Modelling
(Source: Authors' own research results)

The first vertical line is the month when the first COVID-19 vaccine was approved in Europe, while the second one is February 2022, when Russia invaded Ukraine. As we can see from Figure 4, the evolution of the topics is strongly linked to the main events that happened during the last couple of years. For example, the word *inflation* seems to be relatively steady during the pandemic. However, it has clearly increased since the beginning of the war, and then again, after the situation flattens, the probability of the word inflation being in the speeches of the ECB flattens itself. Other words, such as *financial* and *interest*, have increased their frequency inside the topic after the beginning of the war.

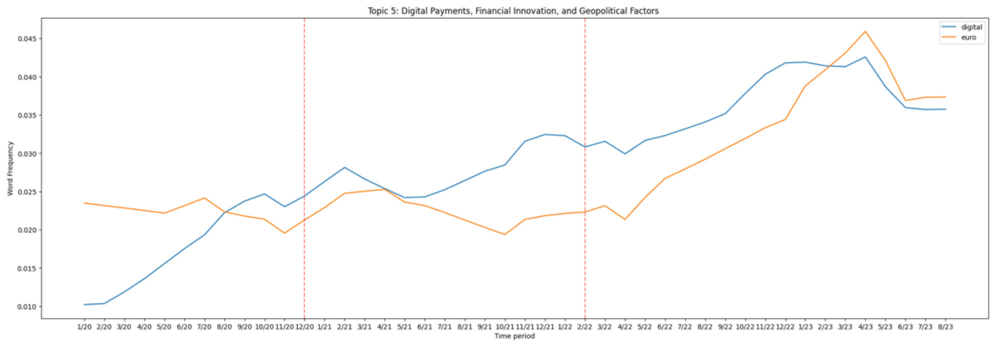

Figure 5. Topic 4 Dynamic Modelling
(Source: Authors' own research results)

Let's look at the evolution of Topic 4. We can see that the discussions about the digital euro are steadily increasing since the pandemic began. However, mostly, they almost doubled during the start of the war, which might be a little counterintuitive since the pandemic seemed to have been the most significant push for a digital currency inside the European Union.

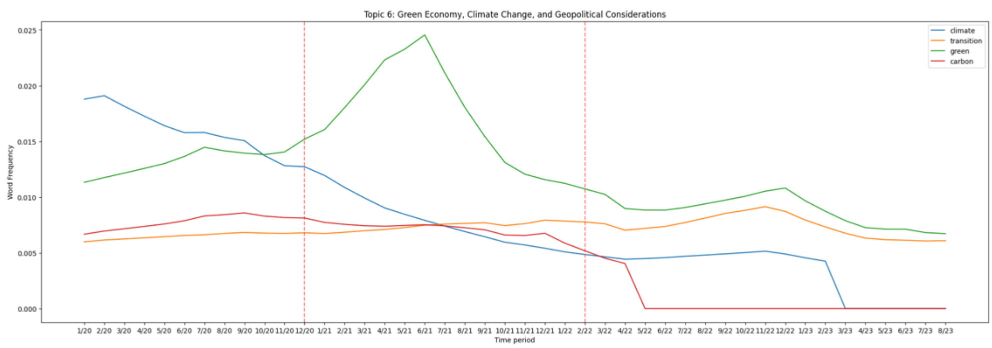

Figure 6. Topic 6 Dynamic Modelling
(Source: Authors' own research results)

Another interesting evolution to see is the evolution of Topic 6, namely the evolution of the speeches regarding pushes for a greener economy and the issue of climate change. It is pretty clear from the DTM analysis that since the beginning of the war, speeches regarding carbon emissions and the climate dropped sharply, while speeches about a green economy seem to be steadily decreasing and flattening right before and after the war. It appears that the war substantially impacted the evolution toward a green economy, which can pose significant problems for the future.

Conclusions

To conclude, we would like to point out the main contributions and limitations of the current paper to the economic literature. First of all, as we already mentioned in the corpus of the paper, there has already been work that correlated the ECB speech data sentiment with the economies of EU countries. With this in mind, it is almost apparent why it is necessary to have quantifiable techniques to analyze this data and the topics of discussion in this data. We consider this information important for investors, other economic actors, and the economy as a whole. Second, by analyzing how the speeches evolve and considering critical historical events, dynamic topic modeling can be seen as the ground to build future work that could use topic models as the input for different inferential models. Third, finding out the main policy directions of the ECB and the response their leadership took in the time of crisis can help policymakers make better future financial policy decisions.

As a main limitation of the study, we must point out the probabilistic nature of LDA, which can make the model less robust regarding changes in the dataset.

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