The similarity of ECB's communication (Paper Replication)

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Code Github: Here

Contents

1 Introduction

Monetary policy, crucial for economic stability, involves diverse central bank communications. Our study replicates and extends Amaya and Filbien (2015)'s work on ***"The Similarity of ECB's Communication"*** which gives a attempt on how the ECB speeches can be analyzed to see its influence in the financial markets and its impact on investor behavior. By following the original methodology of this paper, we look to analyze the linguistic patterns of ECB communications. To do so, first we collect ECB statements using web scraping techniques, and compute the Jaccard similarity score. We expand the research of the paper, by proposing a sentiment score improvement by using a deep learning approach such as BERT model and more rule-based approach with VADER algorithm. that were later compared to highlight the strengths and limitations of each method. In addition, we also wanted to extend the analysis to examine if ECB's monetary policies align with the FED's, given the FED's earlier announcements and the distinct European and American markets. We also questioned if sentiment analysis can predict interest rate highlighting its relevance as global markets and analytical techniques evolve, crucial for financial market participants.

2 Paper Replication

2.1 Web Scrapping

Our primary objective was the automated extraction of ECB statements available online, which is a rich source of insights into the bank's economic and policy orientations. Utilizing the web automation library Selenium and *BeautifulSoup* , we configured a Chrome WebDriver to navigate and retrieve data from specified URLs that we already scrapped before. This process involved iterating over each link, ensuring complete page load, and using BeautifulSoup to extract the essential content from the html source code. Subsequently, the harvested data comprising dates, links, and content were systematically stored in our DataFrame for data manipulation.

The next phase involved data preparation, the Q&A sections were dropped, and the introductory redundant phrases were removed. we implemented content cleaning, though removing punctuation and stop words. We created a function to further sanitize the 'content' column entries. Moreover, we created a column with the tokenized content of every ECB statement. Finally, an additional column that contains the stemmed words of every ECB statement was added for sentimental analysis purposes.

2.2 Similarity and Pessimism

In our study, we set out to measure the similarity of consecutive statements from the ECB to track changes in their rhetoric over time. To do so, we employed the Jaccard index, a statistical tool that gauges similarity by comparing the intersection and union of two data sets. We created a function to identify consecutive pairs of words (bigrams) in the pre-processed text and then calculated the Jaccard similarity for these bigrams between each pair of successive statements.

Additionally, we sought to quantify the level of pessimism in the ECB's statements. Utilizing the Loughran-McDonald sentiment word lists, known for their application in financial contexts, we identified positive and negative words within the statements. We calculated two pessimism scores: a score using the same method used in the paper and another using an advanced deep learning model (BERT). For visual representations of these analyses, see Figures A0.1 and A0.2 in the Appendix.

2.3 Variables

As we extend the period of study; We study statements from July 1997 to Octobre 2023. We use the same variables as those used by the other except the European Index due data sourcing difficulties, we used the MSCI EURO index instead. The Variables that are used in the paper such the Cumulative absolute returns, similarity, the log time and so on were also created using the methods followed by the paper. Due to the unavailability of public data about the output gap in the Euro Zone, we have opted to estimate it (see notebook Modelling).

2.4 Regressions

By employing a similar OLS regression framework, we dissect the relationship between economic indicators—such as the Output Gap and Inflation—and their influence on market dynamics, as reflected in the Adjusted R-squared values (Table A0.1 and A0.2 in appendix). We then integrate variables like Pessimism and Interaction effects (Tables A0.3 and A.04), delving into the subtleties of economic communication patterns. The incorporation of the Bert Model in the final tables (Tables A.05 and A.06) is to do a more sophisticated analysis, offering a nuanced perspective on the intricate interdependencies of these indicators. Each column within the tables corresponds to specific regression equations, methodically revealing the multifaceted influences on market behavior and the distinct communication strategies employed by central banks. These equations are available directly in the notebook where we can also find the distribution of the change in ECB main refinancing operations rates announcements.

2.5 Discussion

Our study delves into the European Central Bank's (ECB) communication and its impact on financial markets, specifically using the MSCI EURO index as a reference and estimating the output gap.

In our linguistic analysis, we used the Jaccard index to assess shifts in the ECB's communication. However, this method might be too simplistic and may not fully capture the nuances in the ECB's language. Also, our sentiment analysis, reliant on predefined lexicons, has its limitations, reminding us of the challenges in accurately processing and interpreting language.

To advance our research, we introduced non-linearity and incorporated a more sophisticated tool, BERT (Bidirectional Encoder Representations from Transformers), for sentiment analysis. This method provides a deeper, more nuanced understanding of the ECB's communication style, potentially offering more precise insights.

Although our approach has certain limitations, it marks a significant step in analyzing central bank discourse. It opens up new avenues for exploration and sets a foundation for future studies in this area.

3 Paper Extension: Sentiment score improvement

3.1 VADER Algorithm

3.1.1 Model Description

VADER (Valence Aware Dictionary and Sentiment Reasoner) is a pre-built, lexicon and rule-based sentiment analysis tool designed for analyzing text data in natural language. It is specifically crafted to handle sentiments expressed in social media texts, as it incorporates features like handling emoticons, capitalization, and context-based sentiment scoring. The lexicon assigns polarity scores to words, indicating the positive or negative sentiment conveyed by each word. These scores range from -1 to 1, where -1 represents extreme negativity, 1 represents extreme positivity, and 0 represents neutrality.

3.1.2 Vader implementation

To implement the Vader algorithm I use the NLTK library.Indeed, VADER is implemented in Python and is part of the NLTK (Natural Language Toolkit) library.

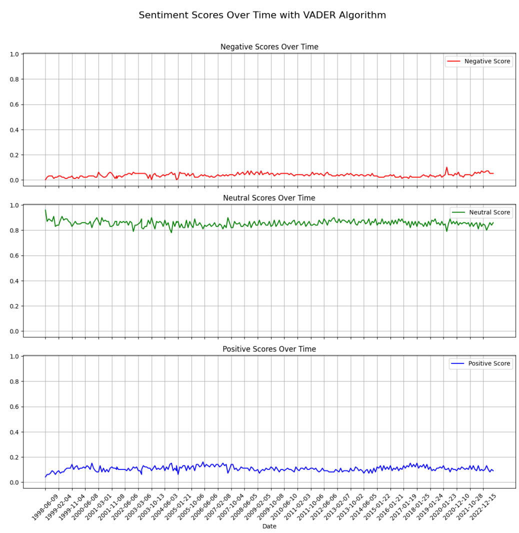
To do so, we implement model as follow:

1. Split the text into sentences based on punctuation '.'
2. Compute the sentiment scores (Negative, Neutral and Positive) for each sentence
3. Create a dictionary to store sentence content and its associated sentiment scores

4. Compute average sentiment scores
5. Determine the overall sentiment of the ECB statement (positive, neutral, or negative) based on average scores computed at the previous step using a majority vote. (See appendix)

3.1.3 Results

Figure 3.1: Vader predictions over the time



Overall, we can see that the 3 scores are remains stable over time. In addition, the scores for negative and positive feelings are close to 0. Conversely, the score for neutral sentiments is close to 1. Hence, we can deduce that the model does not succeed in discerning the sentiments in the ECB statements because we can see that it predicts the same score every time for the 3 feelings. We expected the model to detect negative sentiment in 2008 due to the financial crisis, and in 2022 when Russia invaded Ukraine. These events caused interest rates to rise and these very negative periods were not identified by the model. Therefore, the model does not seem to be able to correctly identify the sentiments behind the ECB's statements.

3.2 BERT Model

3.2.1 Model Description

After a quick review of the scientific literature, we can learn that the state-of-the-art models for sentiment analysis are those based on a transform architecture such as the BERT model. BERT is built upon the Transformer architecture, which was introduced in the paper ***Attention Is All You Need*** by Vaswani et al. (2017). BERT is a significant model in NLP based on the Transformer architecture. BERT's innovation lies in its attention mechanism and two-step training process. Initially, it's pre-trained on a vast text corpus using tasks like Masked Language Model (MLM) and Next Sentence Prediction (NSP). This pre-training enables it to understand language contextually. Subsequently, BERT can be fine-tuned for specific tasks like sentiment analysis on smaller datasets. The bidirectional nature of BERT ensures it considers both preceding and following words to understand context. Furthermore, BERT's foundation is the Transformer architecture, emphasizing the importance of attention mechanisms which allows it to weigh the significance of different words in a sentence when processing each word.

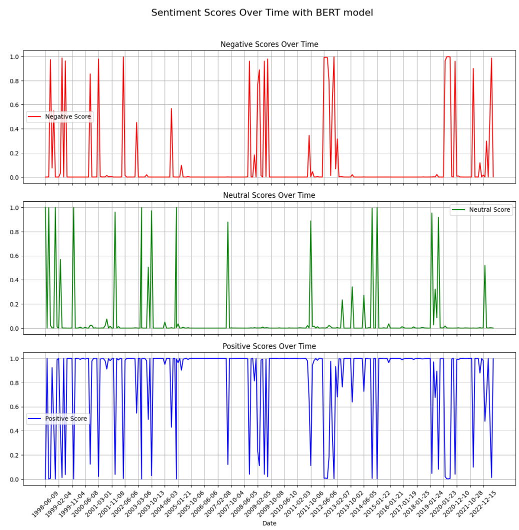
3.2.2 BERT implementation

The model we use is a BERT model fine-tuned on a corpus of financial news for sentiment classification task in order to improve the computation of the sentiment score associated with each ECB statement. To do so we use the 'mrm8488/distilroberta-finetuned-financial-news-sentiment-analysis' from 'HuggingFace' library and process the following step:

1. Tokenize the input text
2. Forward pass through the model (Ensure no gradient is computed)
3. Get the logits from the output (after the forward pass in the neural network)
4. Convert logits to probabilities using $softmax()$ function (because we want to obtain a probability between 0 and 1 for each class)
5. Extract negative, neutral, and positive scores based on the model's output structure
6. Save the outputs on a dataframe (See appendix)

3.2.3 Results

Figure 3.2: BERT predictions over the time



Unlike the VADER model, the BERT model seems to be much better at discerning positive and negative sentiment across the ECB statements. For example, during 2008 and 2009 we consistently find that the positive sentiment score is close to 0 and the negative sentiment score is close to 1, which is consistent with reality as it corresponds to the 2008 financial crisis. Similarly, we observe the same thing for the beginning of 2022, which corresponds to the start of Russia's invasion of Ukraine. These two events are mentioned in the ECB's speeches to explain the rise in inflation rates, which is a very negative phenomenon because it affected economic activity of the world.

In summary, our study shows that new approaches based on Deep Learning (i.e. Transformer architecture) outperform traditional NLP approaches based on the use of sentimental word dictionaries. Deep learning approach are more suitable on sentiment task analysis in case of long dependencies between words and very specific vocabulary (in our case financial terms) and rule-based models are typically designed based on specific rules, criteria, or dictionaries, making them less adaptable to new or unseen data outside their predefined scope. Conversely, rule-based model are usefull when we don't have access to labeled data and when we want to understand clearly how sentiments are determined (i.e explainable model), making it easier to interpret the results and validate the sentiment analysis process.

4 Paper Extension: Does the ECB Follow the Fed?

4.1 Hypothesis

The relationship between the European Central Bank (ECB) and the Federal Reserve (Fed) in monetary policy-making has been extensively studied, with various findings suggesting a complex dynamic. Belke and Gros (2005) explore whether there is a one-way influence from the Fed to the ECB and find evidence to the contrary. Similarly, Ullrich (2003) analyze the policies of the two institutions using Taylor rules, indicating an influence of the Fed's policy on the ECB after 1999. Such findings challenge the predominant assumption of the Fed's unilateral influence over the ECB. Our extension seeks try into this complex relationship, examining the extent to which the ECB has charted its own course or shadowed the Fed's footsteps in the intricate dance of monetary policy based on sentimental analysis.

In our report, we have decided to focus on the ECB's refinancing rates between 2012 and 2023 without including the deposit rates of the marginal lending facility and the deposit facility.

4.2 Results

Granger causality, focusing on predictability rather than economic causality, led us to analyze individual time series separately before comparing patterns.

The comprehensive VAR analysis, including Impulse Response Functions (IRFs), Forecast Error Variance Decomposition (FEVD)A0.8, and Ljung-Box test results, provides a multifaceted view into the monetary policy mechanisms of the Federal Reserve (Fed) and the European Central Bank (ECB). The VAR model's coefficients and the IRFs suggest that while both central banks consider similar economic indicators, they respond to shocks in their respective economies distinctly. The Fed's reactions appear more insulated, with policy rate and inflation largely driven by their own lagged values, suggesting a methodical approach to policy adjustments. Conversely, the ECB's IRFs indicate a broader sensitivity to economic conditions, manifesting a more interdependent and possibly more reactive policy stance.

The FEVD plots underscore this difference, with the ECB A0.6 showing a higher degree of interconnectedness between economic indicators, especially in the later periods. This reveals a more complex dynamic where the ECB's policy rate and inflation are influenced by a broader set of economic variables, unlike the Fed's more self-contained dynamics.

The Ljung-Box test results corroborate these findings, where significant autocorrelation in the ECB's model residuals for key variables like the policy rate and inflation rate point to more intricate temporal structures not captured by the VAR model. This contrasts with the Fed's results, which indicate a generally adequate model fit except for the neutral score.

Collectively, these econometric insights reveal that the ECB operates with a distinct set of policy dynamics and does not merely emulate the Fed. The ECB's monetary policy is characterized by a higher degree of responsiveness to a complex interplay of economic indicators, affirming its autonomy in the global economic landscape. This independent stance is crucial, considering the different economic conditions and objectives that the ECB must navigate compared to the Fed. Therefore, in response to the initial question, the ECB does not simply follow the Fed; it charts its own course in response to the economic climate of the Eurozone.

5 Paper Extension: Can rates be predicted by sentimental analysis ?

5.1 Hypothesis

The findings from Hayo and Neuenkirch (2010) research indicate that communications from the Federal Reserve, especially through less formal channels like speeches by the Governors and Presidents of the Federal Reserve, provide valuable insights into upcoming monetary policy decisions. This spurred us to investigate whether a similar pattern holds true for the European Central Bank (ECB) during a distinct timeframe (2012-2023).

We decided to use the same method as Petropoulos and Siakoulis (2023) and to use different machine learning process to determine the most relevant one, their results highlighted the XG boost model. Our idea is to compare if sentimental analysis could be an unique variable to predict future rate as in the speech, there are sometimes indications of forthcoming economic indicators (inflation, growth for example) or not. Our hypothesis is that, depending on the model, this is possible, but that some models will perform much better with other variables.

5.2 Comparison of the models

Table 5.1: Model Performance Comparison Based on MSE

Model	Infl + GDP	Inflation + Score	Only sentimental score
Linear Regression	0.115617	0.172140	0.169893
Random Forest	0.004317	0.031099	0.188864
XG boost	0.027264	0.035015	0.029624
Deep Neural Network (Loss)	0.012438	0.077615	0.157442

Table 5.2: Model Performance Comparison Based on R^2

Model	Infl + GDP	Inflation + Score	Only sentimental score
Linear Regression	0.273216	-0.082088	-0.067959
Random Forest	0.972861	0.804512	-0.187214
XG boost	-0.223796	0.779892	0.813779

5.3 Results

The effectiveness of sentimental analysis in predicting rates is contingent on the chosen model. Without sentimental analysis, Random Forest is superior, boasting an R^2 close to perfection, signifying strong predictive capabilities. Incorporating both inflation data and sentimental analysis, model performance generally dips; however, Random Forest and XG Boost sustain commendable prediction accuracy, with XG Boost displaying an enhanced fit. Utilizing only sentimental analysis, XG Boost excels with a high R^2, suggesting adeptness in rate prediction from sentiment data alone, whereas Random Forest's negative R^2 reveals a fit inferior to a naive mean model.

In summary, while sentimental analysis exhibits potential for rate prediction, its success varies with the model. XG Boost emerges as particularly adept, harnessing sentimental data to improve predictions. Linear Regression and Random Forest seem less apt when relying solely on sentimental analysis but may yield some predictive value when combined with other data, like inflation rates. It's crucial to acknowledge that model performance is multifaceted, influenced by the quality of sentimental analysis, data nature, and model specifics.

6 Conclusion

In conclusion, our study commencing with meticulous web scraping for data collection and progressing to a detailed evaluation of similarity and pessimism in ECB statements. We enriched our analysis by leveraging both BERT and VADER algorithms to dissect the ECB's sentiments, unveiling intricate insights. This was further augmented by a comparative analysis of ECB and Fed policies using VAR analysis, and an exploration of the predictive capabilities of sentiment analysis on interest rates. Our findings corroborate the existing scientific literature, particularly spotlighting the transformative architecture of the BERT model as a more effective alternative to traditional sentiment dictionary-based methods. The innovative attention mechanism of BERT has been a game-changer in NLP, enabling models to grasp more profound contextual nuances from text data.

Nevertheless, our study acknowledges certain limitations, notably the exclusion of broader economic indicators (additionally to inflation and GDP) from our sentiment analysis model. This gap indicates a promising direction for future research, suggesting that incorporating these macroeconomic factors could further refine and enhance the predictive accuracy of the predictive model.

References

Amaya, D. and Filbien, J.-Y. (2015). The similarity of ecb's communication. *Finance Research Letters*, 13. Posted: June 9, 2015. Last revised: June 11, 2015.

Belke, A. and Gros, D. (2005). Asymmetries in the trans-atlantic monetary policy relationship: does the ecb follow the fed? *Journal of Economics and Business*, 57(5):368–387.

Hayo, B. and Neuenkirch, M. (2010). Do federal reserve communications help predict federal funds target rate decisions?

Petropoulos, A. and Siakoulis, V. (2023). Can central bank speeches predict financial market turbulence? evidence from an adaptive nlp sentiment index analysis using xgboost machine learning technique. *Journal Name*.

Ullrich, K. (2003). A comparison between the fed and the ecb: Taylor rules. *CESifo Forum*, 4(2):15–24.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. *arXiv preprint arXiv:1706.03762*. Revised 2023.

Appendix

Variable	(1)	(2)	(3)	(4)
Intercept	-1.5282***	-7.4334***	-6.8601***	-1.5282***
	(0.000)	(0.000)	(0.000)	(0.000)
Time		0.7041***	0.6318***	
		(0.000)	(0.000)	
Time (count)				
Output gap	0.0003***		0.0002**	0.0003***
	(0.000)		(0.002)	(0.000)
Inflation	-0.0972**			-0.0972**
	(0.025)			(0.025)
Delta MRO	1.4852*		0.0912	1.4852*
	(0.016)		(0.848)	(0.016)
Adjusted R2	11.6%	27.8%	30.0%	11.6%

Table A0.1: OLS Regression that explains similarity

Variable	(11)	(12)	(13)	(14)
Intercept	-1.5282***	-7.4334***	-7.4334***	-1.5371***
	(0.000)	(0.000)	(0.000)	(0.000)
Output Gap	0.0003***			
	(0.000)			
Inflation	-0.0972**			-0.0761**
	(0.025)			(0.050)
Change MRO Rate	1.4852**			
	(0.016)			
Log Diff		0.7041***	0.7041***	
		(0.000)	(0.000)	
Adjusted R-squared	11.6%	27.8%	27.8%	1.1%

Table A0.2: Extention of the first OLS Regression

Variable	(6)	(7)	(8)	(9)	(10)
Intercept	0.0320***	0.0305***	0.0320***	0.0319***	0.0344***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pessimism	0.0094				
	(0.192)				
Pessimism × similarity			0.0313	0.0301	0.0333
			(0.212)	(0.247)	(0.200)
Output gap		1.000e-6		1.000e-6	2.000e-6
		(0.507)		(0.615)	(0.373)
Inflation		0.0005		0.0001	-0.0012
		(0.725)		(0.944)	(0.384)
Delta MRO		-0.0357*		-0.0337	
		(0.095)		(0.116)	
Adjusted R2	0.3%	0.6%	0.2%	0.8%	0.2%

Table A0.3: OLS Regression that explains CAR

Variable	(15)	(16)	(17)	(18)	(19)
Intercept	0.0320***	0.0305***	0.0321***	0.0324***	0.0348***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pessimism 2	0.2132				0.0621
	(0.106)				(0.772)
Pessimism × Interaction			0.9707*	0.9240*	0.8191
			(0.069)	(0.095)	(0.347)
Output Gap		1.323e-6		8.481e-7	1.471e-6
		(0.508)		(0.673)	(0.456)
Inflation		0.0005		-0.000089	-0.0013
		(0.721)		(0.954)	(0.336)
Delta MRO		-0.0356*		-0.0316	
		(0.098)		(0.142)	
Adjusted R2	0.6%	0.6%	0.9%	1.3%	0.5%

Table A0.4: Extention of the OLS Regression that explains CAR

Variable	(6)	(7)	(8)	(9)	(10)
Intercept	0.0294***	0.0305***	0.0305***	0.0298***	0.0323***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pessimism	0.0227***				
	(0.004)				
Pessimism × similarity			0.0542*	0.0505	0.0494
			(0.100)	(0.133)	(0.142)
Output gap		1.323e-6		6.800e-7	1.518e-6
		(0.508)		(0.738)	(0.444)
Inflation		0.0005		0.0004	-0.0009
		(0.721)		(0.771)	(0.514)
Delta MRO		-0.0356*		-0.0362*	
		(0.098)		(0.092)	
Adjusted R2	2.7%	0.6%	0.7%	1.1%	0.4%

Table A0.5: OLS Regression that explains CAR with Bert Model

Variable	(15)	(16)	(17)	(18)	(19)
Intercept	0.0295***	0.0304***	0.0306***	0.0297***	0.0310***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pessimism	0.0226***				0.0453***
	(0.004)				(0.003)
Pessimism × Interaction			0.0538	0.0502	-0.1147*
			(0.102)	(0.136)	(0.074)
Output Gap		1.325e-6		6.860e-7	2.343e-6
		(0.507)		(0.737)	(0.236)
Inflation		0.0006		0.0005	-0.0007
		(0.693)		(0.744)	(0.590)
Delta MRO		-0.0350		-0.0356*	
		(0.104)		(0.098)	
Adjusted R2	2.7%	0.5%	0.6%	1.0%	3.3%

Table A0.6: Extention of the OLS Regression that explains CAR with Bert Model

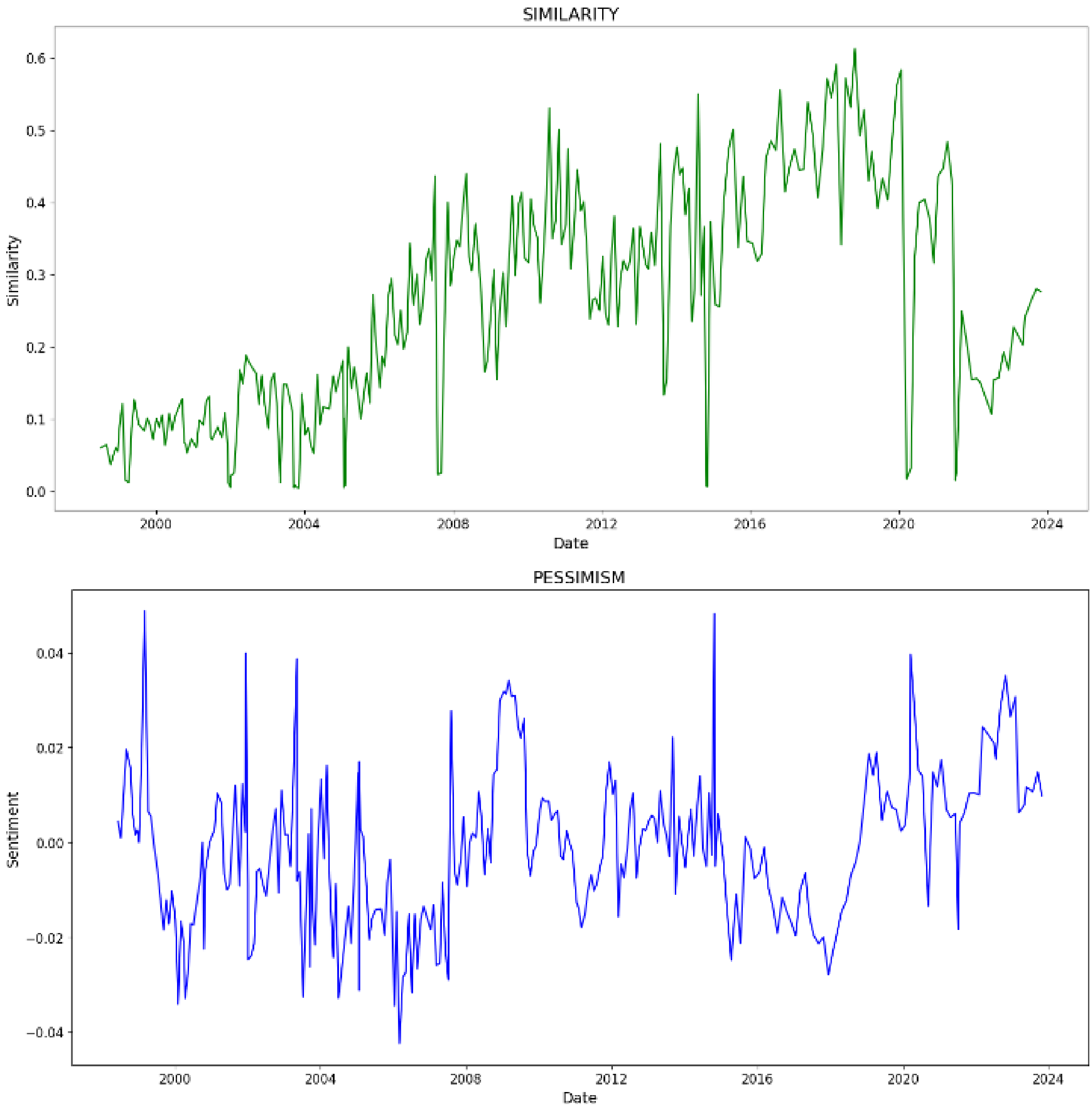


Figure A0.1: Similarity and Pessimism replicating the paper

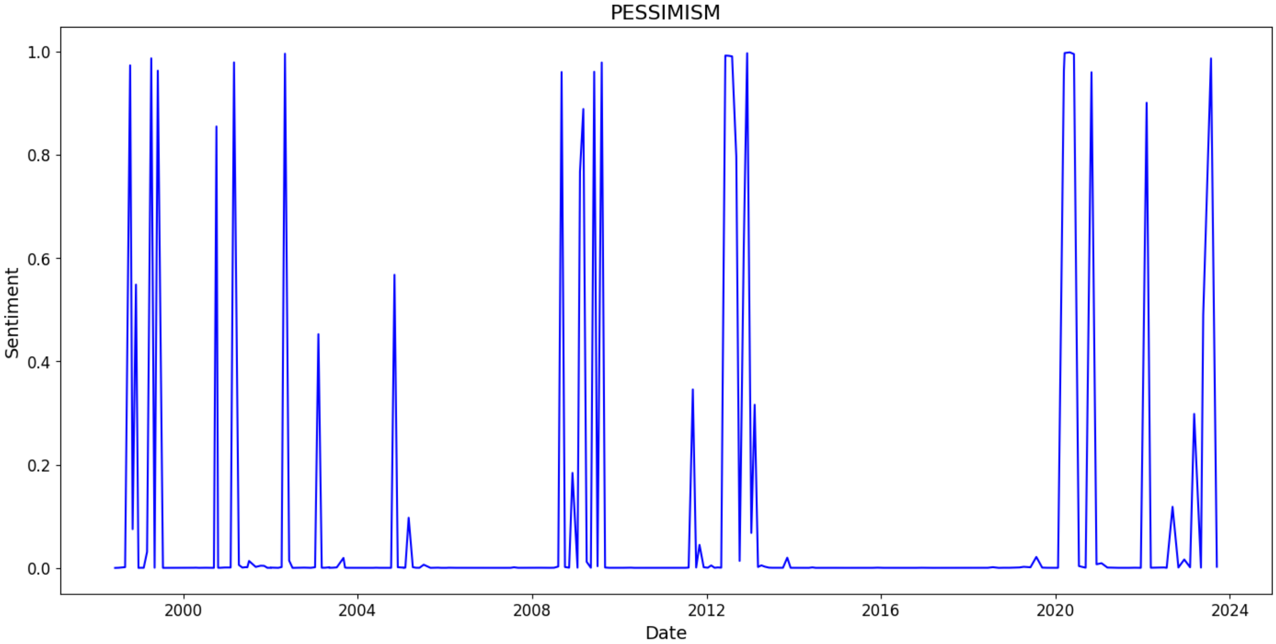


Figure A0.2: Similarity and Pessimism with BERT

Figure A0.3: Vader prediction

	ecb_statement	sentiment_scores_list	vader_sentiment_output	negative_score	positive_score	neutral_score	overall_sentiment	date
0	ECB Press conference: Introductory statement\n...	[{'content': 'ECB Press conference: Introducto...	{'average_positive': 0.04, 'average_negative':...	0.00	0.04	0.96	Neutral	1998-06-09
1	ECB Press conference: Introductory statement\n...	[{'content': 'ECB Press conference: Introducto...	{'average_positive': 0.06, 'average_negative':...	0.02	0.06	0.87	Neutral	1998-07-08
2	ECB Press conference: Introductory statement\n...	[{'content': 'ECB Press conference: Introducto...	{'average_positive': 0.06, 'average_negative':...	0.03	0.06	0.89	Neutral	1998-09-01
3	.\nLadies and gentlemen, in line with our stat...	[{'content': 'Ladies and gentlemen, in line wi...	{'average_positive': 0.07, 'average_negative':...	0.03	0.07	0.88	Neutral	1998-10-13
4	. \nLadies and gentlemen, as in previous month...	[{'content': "Ladies and gentlemen, as in prev...	{'average_positive': 0.09, 'average_negative':...	0.03	0.09	0.87	Neutral	1998-11-03
...	...	...	...	...	...	...	...	...
269	Good afternoon, the Vice-President and I welco...	[{'content': 'Good afternoon, the Vice-Preside...	{'average_positive': 0.13, 'average_negative':...	0.07	0.13	0.80	Neutral	2023-03-08
270	Good afternoon, the Vice-President and I welco...	[{'content': 'Good afternoon, the Vice-Preside...	{'average_positive': 0.1, 'average_negative': ...	0.07	0.10	0.83	Neutral	2023-05-04
271	Good afternoon, the Vice-President and I welco...	[{'content': 'Good afternoon, the Vice-Preside...	{'average_positive': 0.08, 'average_negative':...	0.05	0.08	0.86	Neutral	2023-05-23
272	Good afternoon, the Vice-President and I welco...	[{'content': 'Good afternoon, the Vice-Preside...	{'average_positive': 0.1, 'average_negative': ...	0.05	0.10	0.84	Neutral	2023-07-27
273	Good afternoon, the Vice-President and I welco...	[{'content': 'Good afternoon, the Vice-Preside...	{'average_positive': 0.09, 'average_negative':...	0.05	0.09	0.86	Neutral	2023-09-14

274 rows × 8 columns

Figure A0.4: BERT predictions

	ecb_statement	negative_score	neutral_score	positive_score	sentiment_score	date
0	ECB Press conference: Introductory statement\n...	0.000075	0.999870	0.000055	{'positive_score': 5.517019599210471e-05, 'neu...	1998-06-09
1	ECB Press conference: Introductory statement\n...	0.000334	0.000112	0.999554	{'positive_score': 0.9995539784431458, 'neutra...	1998-07-08
2	ECB Press conference: Introductory statement\n...	0.001494	0.998227	0.000280	{'positive_score': 0.00027962063904851675, 'ne...	1998-09-01
3	.\nLadies and gentlemen, in line with our stat...	0.972774	0.021607	0.005618	{'positive_score': 0.005618469323962927, 'neut...	1998-10-13
4	. \nLadies and gentlemen, as in previous month...	0.074991	0.001537	0.923472	{'positive_score': 0.923471987247467, 'neutral...	1998-11-03
...	...	...	...	...	...	...
269	Good afternoon, the Vice-President and I welco...	0.298129	0.002643	0.699228	{'positive_score': 0.6992283463478088, 'neutra...	2023-03-08
270	Good afternoon, the Vice-President and I welco...	0.000612	0.000281	0.999107	{'positive_score': 0.9991074204444885, 'neutra...	2023-05-04
271	Good afternoon, the Vice-President and I welco...	0.490207	0.002591	0.507201	{'positive_score': 0.5072011351585388, 'neutra...	2023-05-23
272	Good afternoon, the Vice-President and I welco...	0.986191	0.002071	0.011739	{'positive_score': 0.011738589964807034, 'neut...	2023-07-27
273	Good afternoon, the Vice-President and I welco...	0.002222	0.000435	0.997342	{'positive_score': 0.9973422884941101, 'neutra...	2023-09-14

274 rows × 6 columns

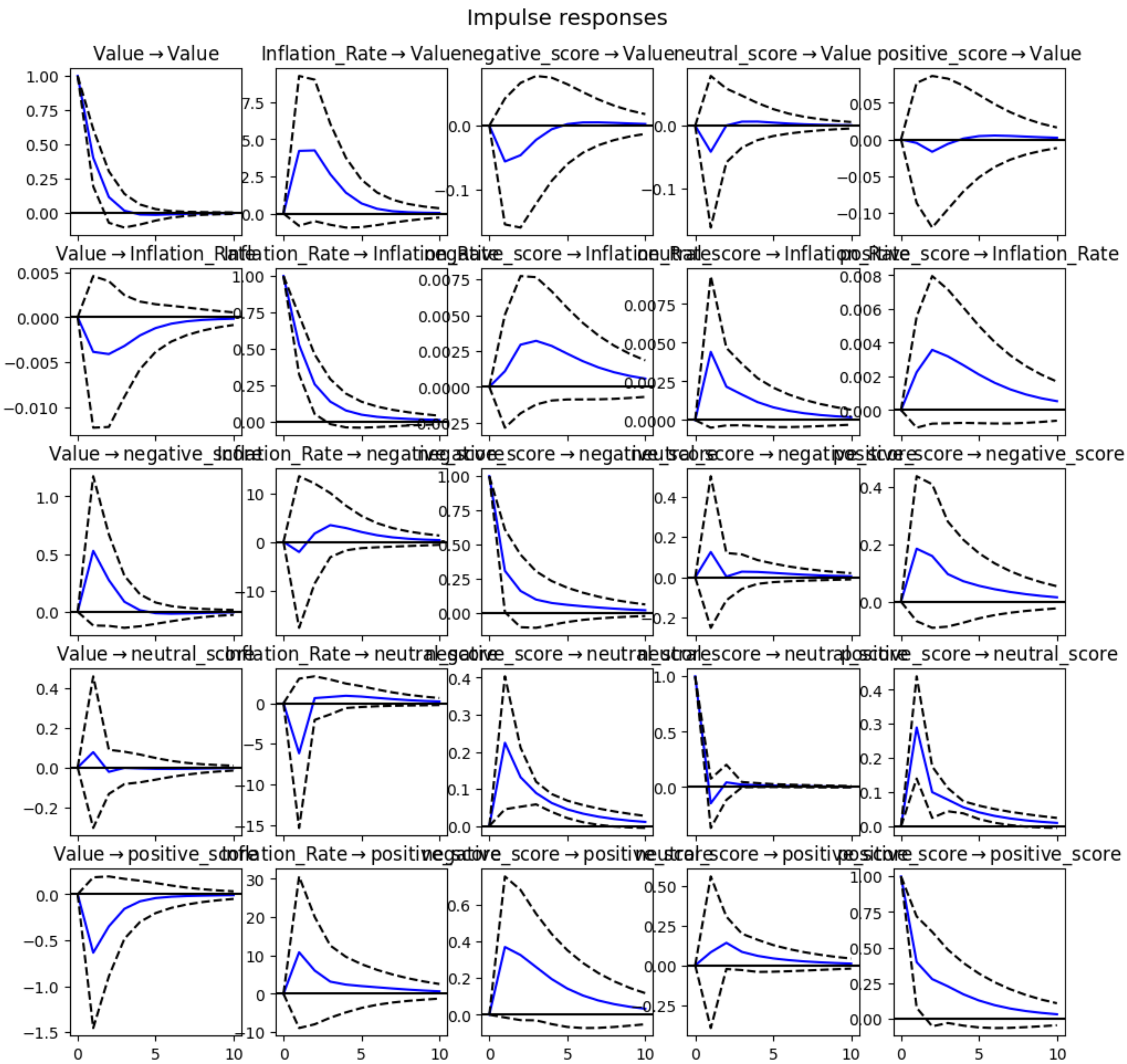


Figure A0.5: IRFs for FED

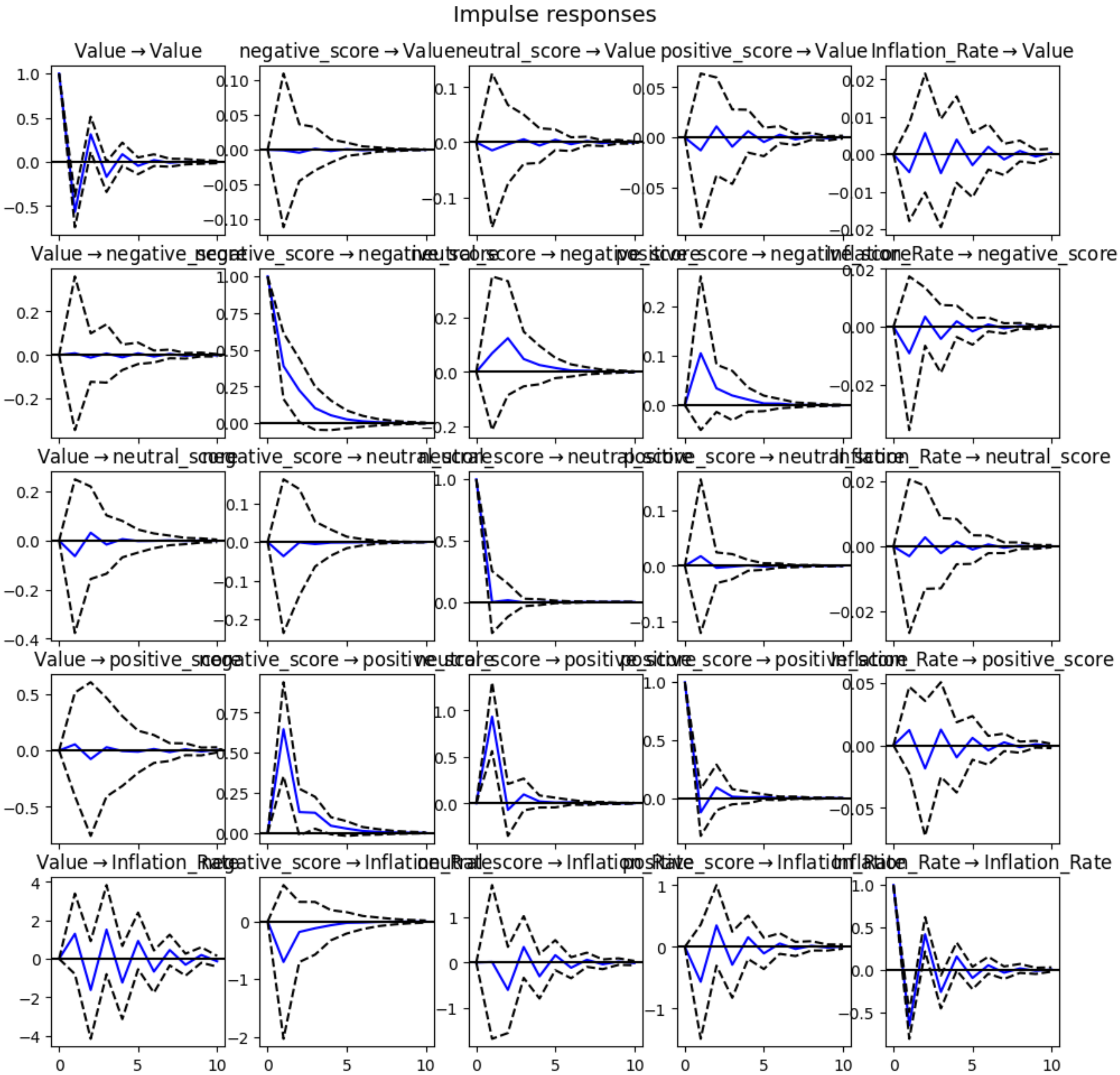


Figure A0.6: IRFs for ECB

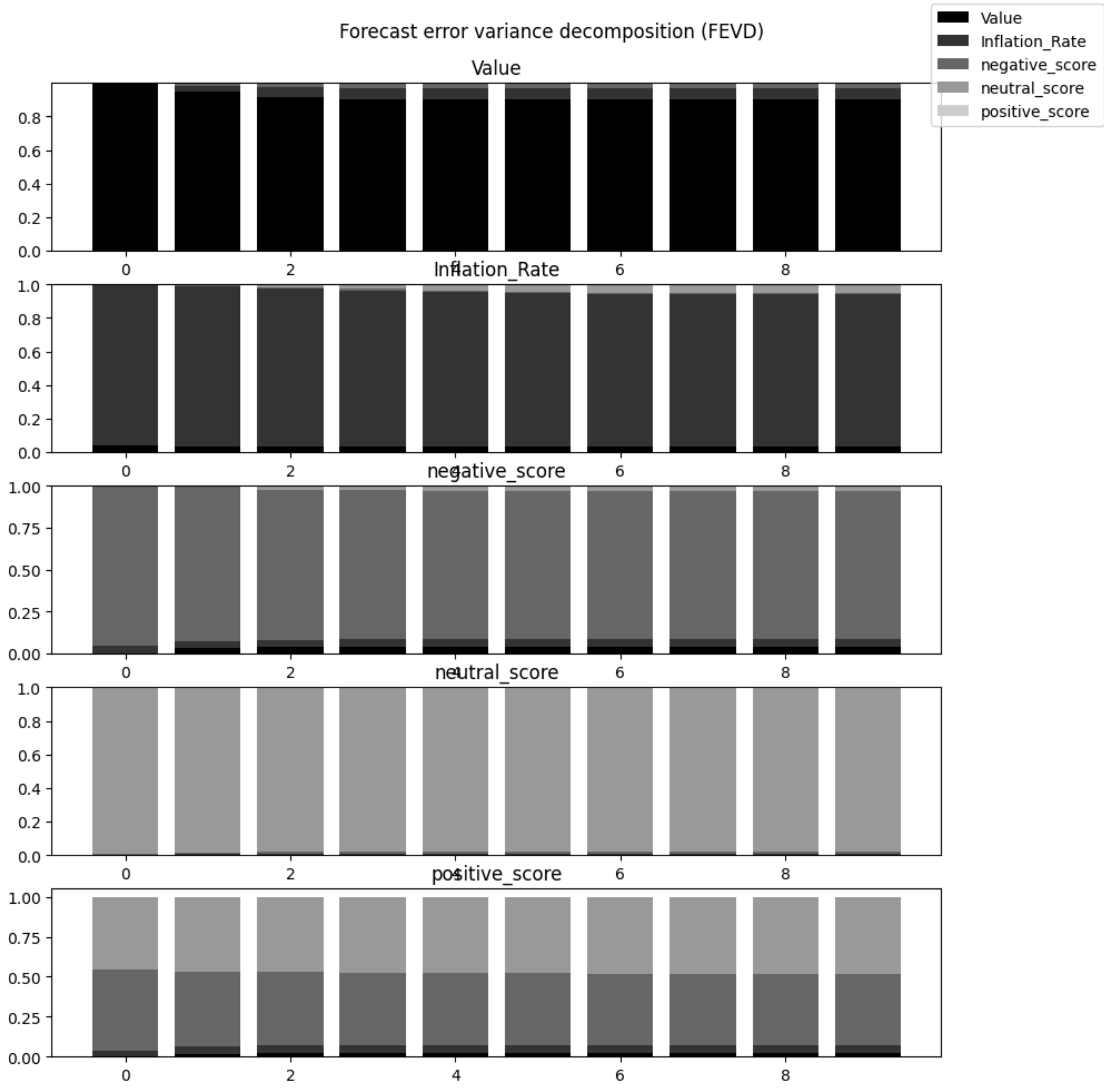


Figure A0.7: FEVD FED

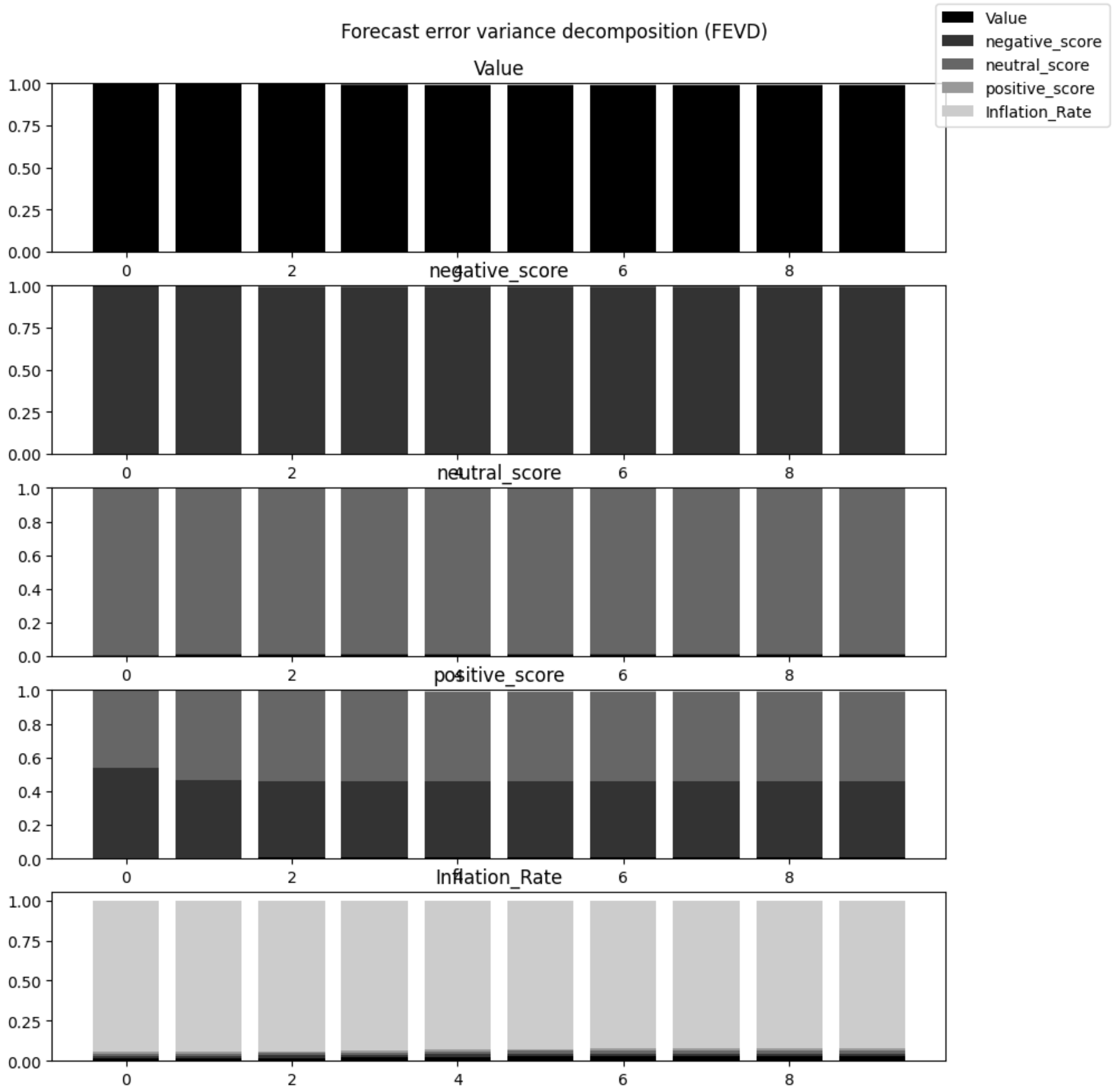


Figure A0.8: FEVD ECB