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Do Central Banks Influence Sustainable Investments? An Analysis of Central Bank Speeches on Climate Change in the Euro Area

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Do Central Banks Influence Sustainable Investments? An Analysis of Central Bank Speeches on Climate Change in the Euro Area.

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November 11, 2025

Abstract

This paper investigates empirically whether central bank communication on climate change influences the pricing of green bonds in the euro area. Using a text-mining approach applied to more than 5,000 central bank speeches between 2016 and 2025, we identify climate-related communications and quantify their sentiment. We then merge these textual indicators with daily prices of green bonds issued across seven euro area countries. Our panel regression results reveal that both the intensity and the sentiment of climate-related central bank communication exert a statistically significant impact on green bond valuations. Domestically delivered speeches are associated with higher green bond prices, whereas foreign and ECB speeches tend to depress them. Positive sentiment amplifies this negative response. Overall, our findings highlight that the tone and content of central bank communication play a non-negligible role in shaping the market for sustainable assets and, by extension, the transmission of climate-related monetary narratives into financial markets.

Keywords: central bank communication, climate change, green bonds, sentiment analysis, text mining
JEL classification: D83, E52, E58, G12, G15, Q54

*The work on this paper has been done independently from my affiliation with the German Bundesbank. The views expressed in this article are those of the authors and do not necessarily reflect those of the German Bundesbank. They should therefore not be reported as such.

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1 Introduction

Environmental sustainability has become a central concern in modern society. Companies are increasingly highlighting their sustainable initiatives, and the topic of environmental sustainability is gaining prominence in financial markets as well. In recent years, central banks around the world have begun to analyze and assess the impact of climate change on the economy and financial markets (Emambakhsh et al., 2022, Estrada et al., 2024, Financial Policy Committee, 2024, Kurian et al., 2023). At the same time, they have started to reflect on their own role in addressing climate change. For example, in 2021 the European Central Bank (ECB) unveiled an action plan to integrate climate change considerations into its monetary policy strategy (European Central Bank, 2021). Furthermore, in 2017 the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) was established with the aim of strengthening the global response to the Paris Agreement and enhancing the financial system's capacity to manage climate-related risks and mobilize capital for green and low-carbon investments within the broader context of environmentally sustainable development (Network for Greening the Financial System (NGFS), 2024).

While there is growing evidence that climate-related central bank communication can influence overall stock market performance (Campiglio et al., 2025, Ebeling, 2024, Neszveda and Siket, 2025), its impact on bond prices — particularly green bonds—remains largely unexplored. This paper aims to address this gap by focusing on the speeches of central banks within the euro area and examining their effects on bonds listed in euro area countries.

It is well established that central banks shape the views and actions of financial markets through their external communications (Altavilla et al., 2019, Blinder et al., 2008, Woodford, 2005). This influence may be particularly pronounced for sustainable investment products such as green bonds. Accordingly, we expect that more prominent central bank communication on climate change will lead to higher green bond prices. Furthermore, drawing on the extensive literature examining the role of sentiment in financial market responses to central bank communication (Alexopoulos et al., 2024, Barry

et al., 2025, Binder et al., 2023, Curti and Kazinnik, 2023, Gorodnichenko et al., 2023), we anticipate that sentiment expressed in central bank communication will play a significant role in shaping green bond market dynamics. To investigate these relationships, we apply a text mining algorithm to a comprehensive corpus of central bank speeches, compile data on green bond markets, and conduct panel regression analysis.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. In Section 3, we outline our empirical approach, including the text mining methodology and the financial market data. Section 4 details the empirical model, while Section 5 presents our results along with robustness checks. Finally, Section 6 concludes the paper.

2 Literature Review

The question of whether banks should take action on climate change has been widely debated in the literature (Bolton et al., 2020, Campiglio et al., 2018, Dikau and Volz, 2021, Hansen, 2022, McKibbin et al., 2022). Nevertheless, there is comparatively little research on the extent to which central bank communication can influence green bond markets. For our study, however, several works are particularly relevant. For instance, Blinder et al. (2008) review the expanding literature on central bank communication and conclude that it can be a powerful and important component of a central bank's toolkit. Kapfhammer et al. (2020) and Ellen et al. (2022) argue that the media—and by extension, public central bank communication—acts as an information intermediary between market participants and the broader economic environment. According to Blinder et al. (2008), central bank communication has the capacity to move financial markets, enhance the predictability of monetary policy decisions, and potentially support the achievement of macroeconomic objectives. They further suggest that official statements, reports, and meeting minutes tend to have the most pronounced empirical effects on financial markets, whereas the impact of other types of speeches is more mixed.

Kapfhammer et al. (2020) employ techniques from the natural language processing literature, leveraging a dataset of approximately 23 million news articles from the Dow Jones Newswires Archive to develop a media-based, country-specific measure of climate change transition risk. For this extensive text corpus, they utilize a neural network to generate word embeddings within the dataset. Notably, their study does not analyze the sentiment associated with climate change coverage, but instead focuses on the specific contexts in which climate change is discussed.

Feldkircher et al. (2021) discuss four distinct approaches to central bank communication that are recognized in the literature, including methods for quantifying both the tone and the content of central bank communications.

To the best of our knowledge, the first study to explicitly examine the link between central bank communication and climate change is Arseneau et al. (2022), who apply natural language processing techniques to analyze how central banks address climate change in their communications. Using a text corpus of over 17,000 central bank speeches, they identify those that are climate-related through an automated, inductive keyword-based approach to topic detection. In this paper, we build on the methodology developed by Arseneau et al. (2022) to identify climate-related speeches, and extend their work by incorporating sentiment analysis and empirically evaluating the impact of these speeches on green bond prices.

Campiglio et al. (2025) examine central bank communication in the context of climate change, building on the methodology of Arseneau et al. (2022) but applying it to a much larger and more diverse dataset of central bank speeches. They distinguish between two dominant narratives: "green finance," which emphasizes support for private market solutions and green financial investments, and "climate-related risks," which focuses on the threats posed by climate change to financial markets and strategies for managing these risks. Their findings indicate that institutional characteristics of central banks - such as mandates, supervisory roles, and country income levels - are more significant drivers of climate communication than the actual economic exposure to climate risks. Another key contribution of their study is the demonstration that climate-related central bank speeches have tangi-

ble effects on financial markets: portfolios of environmentally "green" firms systematically outperform those of "dirty" firms following such speeches, especially when the discourse centers on climate-related risks. In this paper, we adopt a similar approach, but in contrast to their focus on equities and the U.S. market, we concentrate on bonds and restrict our analysis to the euro area.

Despite the contributions of the studies discussed above, several gaps remain in the literature that this paper seeks to address. First, to the best of our knowledge, we are the first to focus specifically on the euro area. Second, our analysis centers on the bond market rather than the stock market. Third, we provide evidence relating specifically to climate-friendly assets. Finally, we account for differences across sectors and countries in our empirical approach.

3 Empirical Analysis

This section outlines the data collection and generation process used for the empirical analysis presented in Sections 4 and 5. The sample period spans from 1 November 2016 to 13 June 2025. Our focus is on seven euro area countries: Germany, Italy, France, Belgium, the Netherlands, Greece, and Ireland. For each of the seven national central banks, as well as the ECB, we classify central bank speeches using a multi-step workflow, which is described in detail below. In the following, we detail the construction of the text mining corpus and the compilation of the financial market data.

3.1 Text Mining Methodology

In this chapter, we describe the methods used to identify climate-related central bank speeches, distinguish these from speeches focused on other topics, and measure the sentiment expressed in these documents. The sample period for the text mining data begins on 7 January 2000, thereby covering a broader time horizon and including more observations than the main sample period of our empirical analysis. We adopt this approach to enhance

the robustness of our text mining algorithms, as the underlying statistical framework performs more reliably with larger datasets. Additionally, this extended period allows us to place our findings within the broader context of the evolution of central bank communication over time.

3.1.1 Data Collection and Preparation

To construct the text corpus, we collect central bank speeches by accessing all English-language speeches, as well as reports, minutes, forecasts, press conferences, and economic reviews made available by the Bank for International Settlements (BIS) on their website.[1] The BIS offers several options for downloading this data. After testing different approaches, we find that the most effective solution is to use a web scraper for the BIS website, for several reasons. First, this method enables us to represent each speech as an individual document, both for analytical purposes and at the technical level. Second, the scraping algorithm allows us to automatically extract and process the metadata associated with each speech. Third, it facilitates double-checking for completeness and consistency within the dataset.

We convert the scraped transcripts from PDF to plain text format using the PDFMiner Python package.[2] With this approach, we successfully transform approximately 97 % of the PDF files into text. To ensure the reliability of this process, we develop and implement a quality control routine aimed at identifying and correcting common issues associated with PDF conversion.[3]

[1]The speeches are collected from national central banks by BIS staff based on their relevance to central bankers and the general public. Translations into English are provided by the national central banks. See: https://www.bis.org/cbspeeches/download.htm.

[2]Comprehensive documentation for the PDFMiner Python package is available at: https://pdfminersix.readthedocs.io/en/latest/.

[3]Decoding PDF documents is widely recognized as a challenging task within the data science community, as the idiosyncratic structure of PDFs is not inherently designed for seamless translation into other file types. While several open-source Python packages have been developed to address this issue, and PDFMiner represents the result of ongoing optimization efforts by the Python community, it is not possible to eliminate errors entirely. To address this, we employ a structured logging and debugging routine within our conversion pipeline, enabling us to detect and correct format translation errors both at the corpus level and for individual documents. We identify PDFs where the conversion algorithm fails, fine-tune the process to minimize failed translations, and achieve a success rate of 97 %. We also draw random samples of documents, manually compare the converted text to

In addition, we extract the date on which each speech was delivered, which is later used to match the transcript data with the corresponding financial time series.

Our corpus comprises 5,602 documents from the 21 central banks within the euro area. As shown in Table 1, approximately 42 % of the speeches in the corpus were delivered by officials from the ECB. In addition to the ECB, the seven countries examined in this study collectively account for a further 41.61 % of the corpus.

Table 1: Composition of the text-mining corpus

Central bank	Speeches	Share (%)
ECB	2,356	42.06
Deutsche Bundesbank	768	13.71
Bank of France	402	7.18
Bank of Italy	393	7.02
Central Bank of Ireland	342	6.11
Bank of Spain	337	6.02
Netherlands Bank	220	3.93
Bank of Finland	186	3.32
Bank of Greece	167	2.98
Bank of Portugal	81	1.45
Austrian National Bank	80	1.43
Central Bank of Malta	59	1.05
National Bank of Belgium	40	0.71
Central Bank of Luxembourg	38	0.68
Bank of Lithuania	35	0.63
Central Bank of Cyprus	28	0.50
Bank of Estonia	22	0.39
Bank of Slovenia	20	0.36
Croatian National Bank	14	0.25
Bank of Latvia	9	0.16
National Bank of Slovakia	5	0.09

the original PDFs, and iteratively refine the algorithm until no errors are detected in the samples.

3.1.2 Text Pre-Processing

Text pre-processing[4] is regarded to be a crucially important step in the text mining process by the literature. Especially for text mining algorithms it is a necessary precondition for robust text analysis. We follow an algorithm that is widely used in the NLP literature, such as in Gentzkow et al. (2019), Ash and Hansen (2023) and Arseneau et al. (2022).

We use the Python spaCy and NLTK libraries, which provide a large variety of useful tools for text mining. We apply these tools throughout the entire text pre-processing workflow.

We start by cleaning the text corpus from uninformative components by removing the unprintable ASCII control characters, which do not represent letters or numbers. Next, we put each word into lower case, thereby enforcing comparability between words and reducing the noise in the text data caused by spelling errors. We also remove punctuation and numbers, since these elements are considered uninformative for the keyword approach and are likely to distort the statistical text analysis.

We tokenize the text, so that each individual word in each document is treated as an individual object (word token) and the entire document as a list of word tokens. We lemmatize the tokens and remove common stop words[5] In order to properly treat phrases, we apply a noun phrase detection algorithm that generates meaningful multi-word tokens, such as "climate change", "financial crisis" or "the world economy". By considering these multi-word tokens in our analysis, we integrate contextual information and thereby increase the effectiveness of our analytical framework. So, the meaning of the words "financial" and "crisis", and of the phrase "financial crisis" is assessed individually in the text mining pipeline.[6] Finally, we filter

[4]Text pre-pocessing refers to algorithms that are applied on text to make it usable as data. Its main purpose is to reduce unhelpful complexity in the text(Gentzkow et al., 2019).

[5]For the stop words removal algorithm, we use the stop words dictionary from the NLTK corpus `https://www.nltk.org/nltk_data/`.

[6]We try out several alternative methods of phrase token detection that all perform worse on our data than noun phrase detection. Many of these methods, like e.g. simple bigram or trigram detection, consume much more hardware resources and produce a lot of non-meaningful tokens. These tokens are not only hardly interpretable but they also

out all single-word tokens that occur less frequently than 100 times in the text corpus, as is regularly suggested in the literature (see Arseneau et al. (2022), among others). In this way, we simplify the data workflow by reducing the amount of input data to be processed, and reduce the noise component in the word count analysis. Typical infrequent words are names of people and places, foreign words or misspellings.

The processed and cleaned text corpus contains 7,664 unique tokens. A statistical description of the token frequencies is given in Table 2. One can see that the distribution of token frequencies is highly skewed – while most tokens emerge in the speeches rather infrequently, the corpus is inflated by a few extremely common tokens. This is a typical observation in large text corpora. An illustration of the most frequent tokens in our corpus is provided in Table 3. The list of unique tokens in combination with the tokenized transcripts mark the starting point for the topic classification algorithm that is necessary to detect the climate-related speeches.

Table 2: Descriptive statistics: *word frequencies on corpus level*

Statistic	Value
Obs.	7,664
Mean	1,008.23
SD	3,337.54
p25	148
Median	270
p75	696
Min	100
Max	87,772

3.1.3 Topic Classification

We obtain a numerical measure of the semantic presence of our topic of interest - climate change - in each speech transcript. To achieve this, we employ a well-established text mining approach: a seed-word-based word scoring technique. Consistent with the NLP literature, we use this popular method

impair the classification algorithm.

Table 3: Top 10 tokens by occurrence count

Rank	Token	Occurrences
1.	bank	87,772
2.	financial	72,504
3.	policy	65,172
4.	not	64,902
5.	euro	54,645
6.	market	54,565
7.	central	51,768
8.	monetary	48,300
9.	risk	46,171
10.	area	45,338

because it is based on a transparent statistical framework, produces reproducible results, and has demonstrated strong performance in low-dimensional classification tasks within large datasets. Following the methodology of Arseneau et al. (2022), we begin by defining a set of seed words, then split the data into two subsets. We calculate topic relevance scores for individual tokens as normalized relative frequencies within these subsets, and subsequently use these scores to assess topic relevance at the document level.

The definition of the seed word marks the starting point. As suggested in Arseneau et al. (2022), we select the bigram "climate change" as the seed word. For each document, we check whether it contains our seed word and split the entire document corpus into two disjoint subsets: S_{Seed} and $\bar{S}_{Seed}$. A document is an element of S_{Seed} if it contains the token "climate change". Otherwise, it is assigned to $\bar{S}_{Seed}$. 389 or 6.94% of the speeches in our corpus contain the seed word and thus belong to S_{Seed}, the remaining 5.213 speeches are classified as $\bar{S}_{Seed}$.

We present the ten most frequent tokens for each subset of the corpus in Table 4a and Table 4b. As shown, the most common tokens are largely the same across both subsets. Aside from the tokens "climate" and "change", the list in Table 4a does not include any words that are specifically related to climate change. This indicates that simple document labels alone are insufficient for identifying topic-specific vocabulary; a more robust technique

is required to accurately determine the relevant tokens.

(a) Top 10 tokens in S_{Seed}

Rank	Token	Occurrences
1.	bank	5,767
2.	risk	5,366
3.	financial	4,700
4.	policy	4,279
5.	climate	4,048
6.	central	3,592
7.	change	3,373
8.	also	3,283
9.	economic	2,693
10.	inflation	2,604

(b) Top 10 tokens in $\bar{S}_{\text{Seed}}$

Rank	Token	Occurrences
1.	bank	82,005
2.	financial	67,804
3.	policy	60,893
4.	euro	52,959
5.	market	52,391
6.	central	48,176
7.	monetary	45,866
8.	area	43,534
9.	risk	40,805
10.	rate	38,542

Table 4: Top 10 tokens by occurrence count (two panels).

So, we continue by calculating a *climate word score* for each word i in the text corpus. We define the climate word score cws_i as

$$cws_i = \log(wf_{i,S_{Seed}}) - \log(wf_{i,\bar{S}_{Seed}}) \tag{1}$$

where $wf_{i,S_{Seed}}$ is the normalized frequency of i in speeches from S_{Seed}, and $wf_{i,\bar{S}_{Seed}}$ the normalized frequency of i in speeches from $\bar{S}_{Seed}$. cws_i provides information on how more likely it is to find a specific word i in a speech transcript where one also find the seed word than finding it in a speech which does not contain the seed word. Words with high climate word scores are therefore likely to be part of the same semantic clusters as the seed word.

Table 5 shows that, on average, tokens in the corpus are unlikely to be associated with a climate-change-related semantic context. This is evident from the fact that the majority of tokens have a climate word score below or close to zero. However, there is a small amount of tokens with high *cws* values, which are likely to be useful for identifying climate-related documents. The ten tokens with the highest *cws*, as well as the ten tokens with the lowest *cws*, are presented in Table 6. Among highest-scored tokens are "climate_risks",

"ngfs" or "lowcarbon", which we would expect in a climate-related central bank speech. These tokens appear to be much more closely aligned with the topic of climate change than those identified in the previous step of the topic detection pipeline (as shown in Table 4).

Table 5: Descriptive statistics: climate word scores (unique tokens)

Statistic	Value
Obs.	7,664
Mean	−0.130
SD	0.722
Min	−4.322
p25	−0.448
p50	−0.087
p75	0.225
Max	9.578

Table 6: Top 10 tokens by climate word score (two panels)

(a) Highest scores

Rank	Token	Score
1.	climate_change	9.578
2.	climate_risks	4.734
3.	naturerelate	4.477
4.	ngfs	4.432
5.	paris_agreement	4.419
6.	lowcarbon	4.189
7.	climaterelate	4.180
8.	greenhouse	4.128
9.	warming	4.086
10.	emission	4.043

(b) Lowest scores

Rank	Token	Score
1.	accession	−4.322
2.	sepa	−4.012
3.	duisenberg	−3.333
4.	money_market	−3.300
5.	islamic	−3.283
6.	ncbs	−3.180
7.	enlargement	−3.175
8.	latvia	−3.098
9.	basel_ii	−3.026
10.	exchange rates	−2.997

Notes: Scores are rounded and printed to three decimals.

After that, we compute *climate speech scores* css_j for each speech j based on the climate word score $css_{i,j}$ of each token i in document j as a weighted average of the word scores of i:

$$css_j = \sum_j (cws_i \times wf_{i,j}) \tag{2}$$

We provide descriptive statistics for the *css* in Table 7. The vast majority of speeches – at least 75 % of the total – have a negative climate speech score, indicating that they are unlikely to be centered on the topic of climate change. So, the documents with $css_j > 0$ and even more so the ones with $css_j > \mu_{css} + 2\sigma_{css}$ display an uncommonly high density of climate-change-related tokens.

Table 7: Descriptive statistics: climate speech scores (speech level)

Statistic	Value
Obs.	5,602
Mean	−0.082
SD	0.131
Min	−0.464
p25	−0.159
p50	−0.104
p75	−0.034
Max	0.713

Figure 1 displays the temporal distribution of speeches, categorized by euro area central banks represented in the green bond dataset. Figure 2 provides an overview of the number of climate-related speeches compared to the total number of speeches over time.

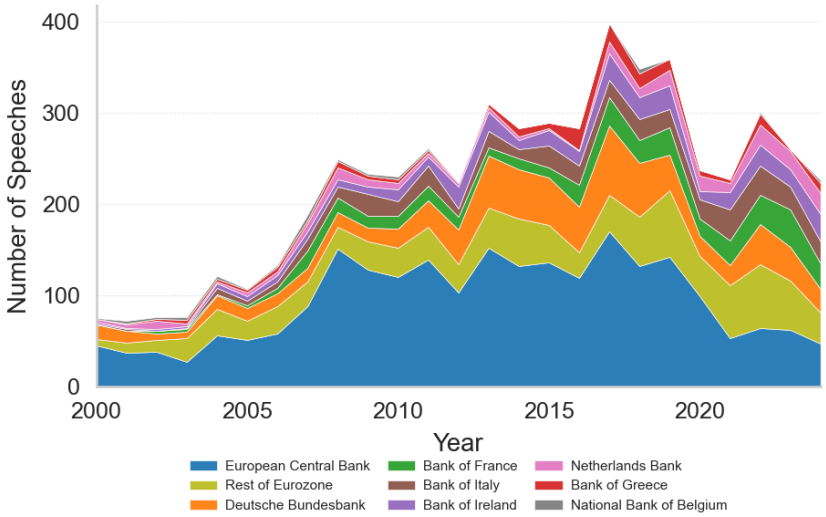


Figure 1: Number of speeches held by different central banks per year

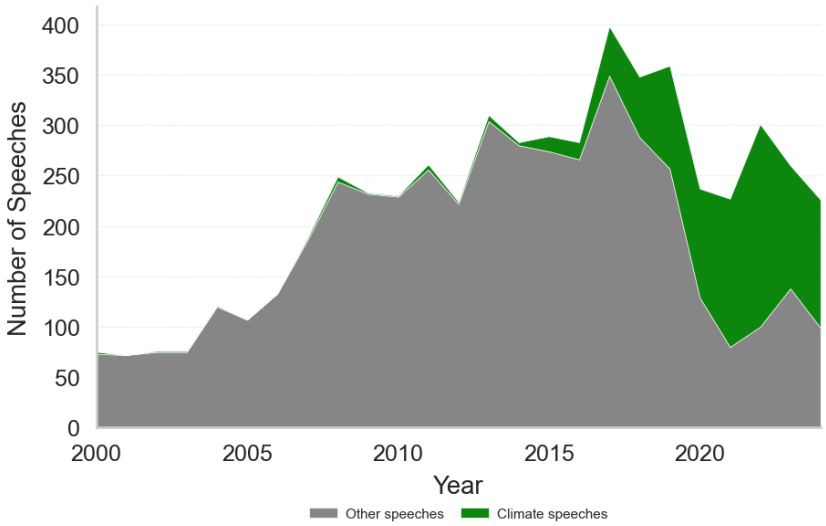


Figure 2: Number of climate speeches and number of non-climate speeches

3.1.4 Sentiment Analysis

We conduct a sentiment analysis for the eight central banks under investigation over the sample period from 1 November 2016 to 13 June 2025, performing the analysis at the document level. This approach allows us to account for the mediating effect of sentiment on the impact of climate-change-related central bank speeches on green bond markets. To this end, we apply the pre-trained bidirectional transformer model FinBERT, as provided by the model's authors on the official FinBERT GitHub repository[7], to our collection of documents. FinBERT is an embeddings-based language model employing the BERT-technology (Devlin et al., 2019) that has been trained on subset of the Reuters TRC2 dataset. It is fine-tuned to detect financial sentiment in text and is increasingly used for sentiment analysis tasks in financial economics research [8] (Araci, 2019). It classifies each document as either "positive", "neutral" or "negative" based on the document's semantic properties. We then conveniently assign the numerical values "1", "0" or "−1" to the respective verbal categories for the econometric analysis.

Figure 3 shows the monthly average sentiment of speeches and the total number of speeches with neutral, negative, or positive sentiment. Throughout the sample period, neutral sentiment dominates most speeches, while positive and negative sentiments occur at similar frequencies. The monthly average sentiment has shifted from slightly negative to slightly positive, peaking in 2021, and has since fluctuated around zero, reflecting near-neutral sentiment overall.

Figure 4 reveals substantial variation in average sentiment patterns among the different central banks. However, the average sentiment time series for each sub-sample generally evolves around a value at or near zero. Notably, the sample-average results are predominantly influenced by the sentiment of ECB speeches. The descriptive statistics for the FinBERT labels are pro-

[7]See https://github.com/ProsusAI/finBERT for the documentation and access to the model.

[8]FinBERT was successfully applied to central bank texts by Kanelis and Siklos (2023) and Barry et al. (2025). Kim et al. (2024) show that FinBERT is superior in performance on FOMC minutes data compared to other LLMs, such as VADER or GPT4.

vided in Table 8. It becomes evident that the mean speech sentiment is close to zero for all central banks except the Bank of France. At the same time, the distribution of sentiment values exhibits considerable variation, with individual speeches occasionally displaying markedly positive or negative sentiment. This variation provides scope for a meaningful interpretation of sentiment values in an economic context.

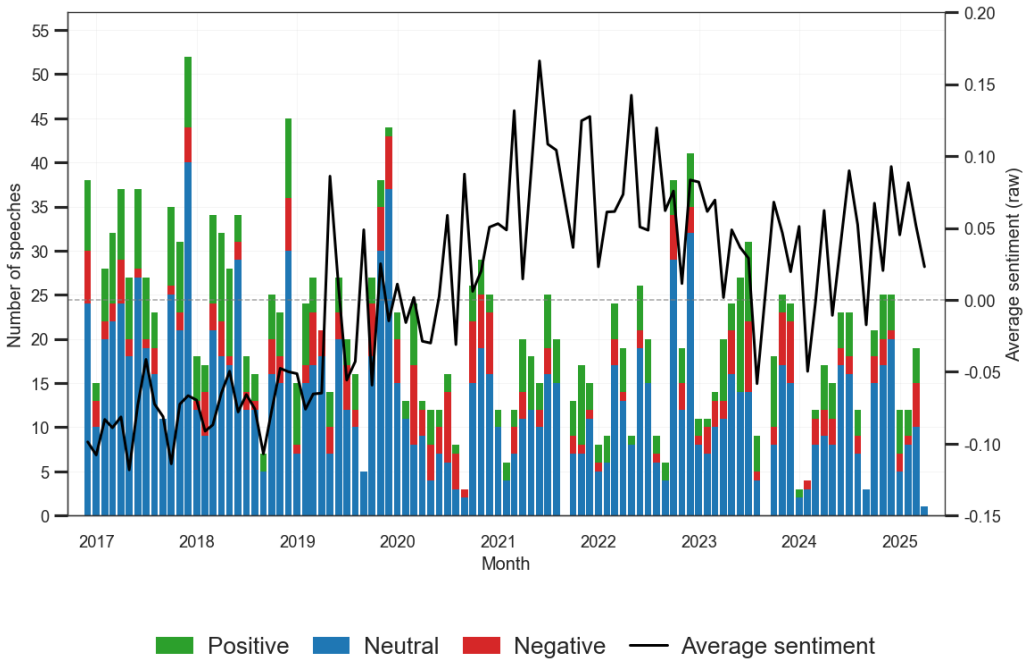


Figure 3: Average monthly sentiment and number of speeches per sentiment class.

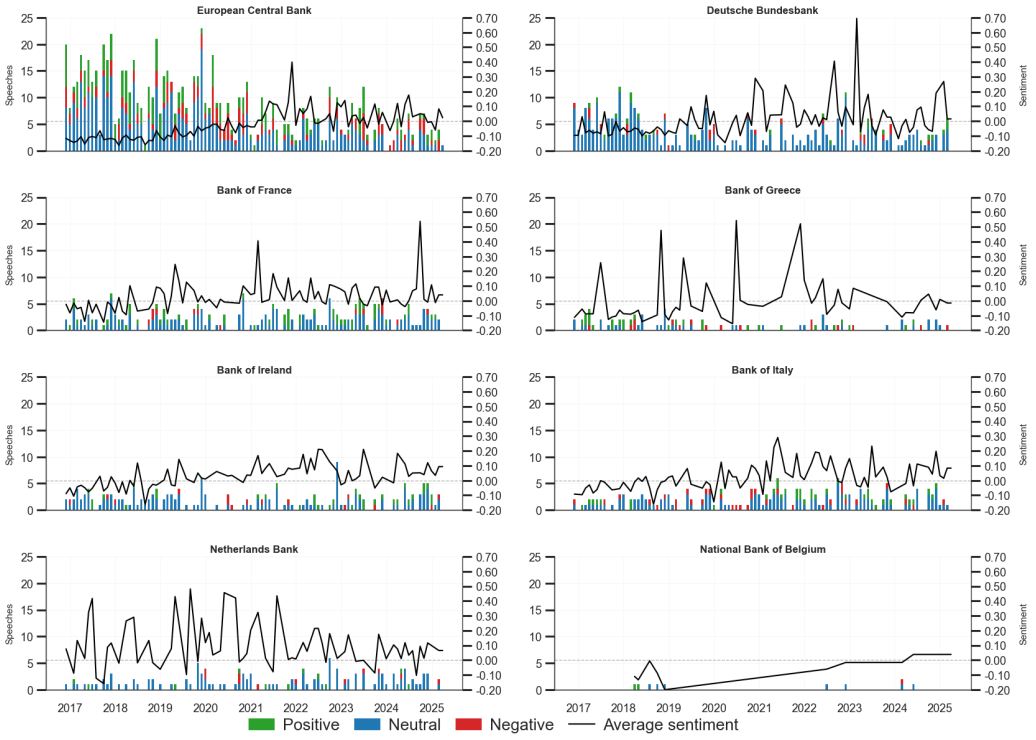


Figure 4: Average monthly sentiment and number of speeches per sentiment class by central bank.

Table 8: Descriptive Statistics of Sentiment Scores by Central Bank

Central Bank	Obs.	Mean	Std. Dev.
ECB	804	0.08	0.67
Deutsche Bundesbank	348	0.00	0.39
Bank of France	241	0.20	0.53
Bank of Italy	203	0.02	0.60
Bank of Ireland	187	0.10	0.50
Netherlands Bank	135	0.00	0.41
Bank of Greece	86	0.14	0.71
National Bank of Belgium	10	0.10	0.57
Total sample	2,014	0.07	0.58

Notes: Sentiment score: *positive*=1, *neutral*=0, *negative*=-1. Sample: $\geq$ Nov 1, 2016; observations on the level of central-bank-specific daily averages.

3.2 Financial Market Data

For the selection of green bonds, all ESG bonds listed in the Green Bond Guide within Refinitiv are used. For a green bond to get in the Green Bond Guide, the Refinitiv Green Bond Process must be completed, for which four mandatory requirements need to be met: First, the security is labeled as green. Second, there should be a framework on which the security is issued. Third, the issuer should make periodic reporting of how the proceeds are being utilized - as long as the instrument remains outstanding. Fourth, the issuer should have a clear framework on how to utilize the proceeds from the offering.

We focus on the euro area and bonds that are denominated in euros. Additionally, the data is confined to "Green Only" ESG bonds, as the impact of central bank communication on the social and governance criteria is explicitly not within the scope of this study. To ensure that the bonds are truly green, we further restrict the selection to bonds certified as green by the Climate Bond Initiative (CBI), thereby excluding all self-labeled green bonds and green bonds that are only CBI-aligned. Since not all euro area countries are domiciles of CBI Certified Green Bonds, the scope of our analysis becomes naturally reduced to the following seven countries: Belgium, Germany, France, Greece, Ireland, Italy and the Netherlands. In total, our dataset encompasses 68 assets, with the highest number of assets (38) being issued in France, and the lowest number of assets (1) being issued in Greece and Ireland, as shown in Table 9.

Depending on the country and the year, the number of green bonds varies. In line with the sustainability trend, the number of green bonds has been increasing continuously and significantly since 2020. The first green bond for which sufficient data is available dates back to 1st November 2016, which is the starting point for our analysis.

Table 9: Number of green bonds by country (domicile)

Country (domicile)	Bonds
France	38
Netherlands	17
Germany	7
Belgium	2
Italy	2
Ireland	1
Greece	1
Total	68

4 Empirical Model

To estimate the effects of climate-related central bank communication on the European market for green bonds, we construct a panel dataset linking daily green bond prices with the outputs of our topic classification and sentiment analysis. The sample period spans from November 1, 2016 - corresponding to the issuance of the earliest bond in the sample - to June 13, 2025.

To represent the topic classification results, we define for each central bank k a time series vector CSS_k (Climate Speech Index):

$$CSS_k := \begin{pmatrix} x_{t=1} \\ x_{t=2} \\ \vdots \\ x_T \end{pmatrix}, \quad T = 2,250 \tag{3}$$

The element x_t represents the communication signal on day t and is defined recursively as

$$x_t = \begin{cases} \overline{css}_{j,t,k}, & \text{if } |J_{t,k}| \neq 0, \\ \overline{css}_{j,t-1,k}, & \text{if } |J_{t,k}| = 0 \wedge |J_{t-1,k}| \neq 0, \\ \overline{css}_{j,t-2,k}, & \text{if } |J_{t-1,k}| = 0 \wedge |J_{t-2,k}| \neq 0, \\ \vdots & \\ \overline{css}_{j,t-n,k}, & \text{if } |J_{t-n-1,k}| = 0 \wedge |J_{t-n,k}| \neq 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Here, $J_{t,k}$ denotes the set of all speeches j delivered by central bank k on day t, $|J_{t,k}$ its cardinality, $\overline{css}_{j,t,k}$ the arithmetic mean of all speech-level climate scores $css_{j,t,k}$ delivered by k on that day. The parameter $n \in \mathbb{N}$ ensures that the most recent non-missing communication value is carried forward in periods without speeches.

Hence, CSS_k reflects a persistent communication signal: it takes the average climate speech score on any given day with a speech and retains this value until a new speech occurs. Prior to a central bank's first speech within the sample period, the index is set to zero.

The corresponding sentiment index $Sent_k$ is defined analogous:

$$Sent_k := \begin{pmatrix} e_{t=1} \\ e_{t=2} \\ \vdots \\ e_T \end{pmatrix}, \tag{5}$$

with

$$e_t = \begin{cases} \overline{sent}_{j,t,k}, & \text{if } |J_{t,k}| \neq 0, \\ \overline{sent}_{j,t-1,k}, & \text{if } |J_{t,k}| = 0 \wedge |J_{t-1,k}| \neq 0, \\ \overline{sent}_{j,t-2,k}, & \text{if } |J_{t-1,k}| = 0 \wedge |J_{t-2,k}| \neq 0, \\ \vdots & \\ \overline{sent}_{j,t-n,k}, & \text{if } |J_{t-n-1,k}| = 0 \wedge |J_{t-n,k}| \neq 0, \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

Here, $sent_{j,t,k}$ denotes the mean sentiment score across all speeches j delivered by central bank k on day t, where sentiment values take the numerical form $\{-1, 0, +1\}$ for negative-neutral, and positive tone, respectively.

For each bond issuer country c, we aggregate the central-bank-specific indices into three categories:

$$CSS_c^{\text{home}} := CSS_k \quad \text{for } k = c, \tag{7}$$

$$CSS_c^{\text{ECB}} := CSS_{k=ECB} \tag{8}$$

$$CSS_c^{\text{rest}} := \frac{1}{N-2} \sum_{r \neq c, r \neq ECB} CSS_r. \tag{9}$$

Analogous definitions hold for the sentiment indices $Sent_c^{\text{home}}$, $Sent_c^{\text{ECB}}$, and $Sent_c^{\text{rest}}$. These aggregates capture, respectively, the communication from the domestic central bank, the ECB, and all other euro area central banks.

To account for conventional macro-financial influences, we include daily yields of ten-year green bonds $y_{c,t}$ for each issuer's home country and the bond-specific bid-ask-spread $BAS_{i,t}$ as measures of liquidity.

We include country and sector dummies to account for time-invariant heterogeneity across issuers and industries. For each green bond i, we define a country dummy D_i^c and a sector dummy D_i^s as

$$D_i^c = \begin{cases} 1, & \text{if bond } i \text{ is issued in country } c \text{ ,} \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

$$D_i^s = \begin{cases} 1, & \text{if bond } i \text{ belongs to sector } s, \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

These dummies are included in the regression to capture unobserved structural differences between countries and sectors that may affect the pric-

ing of green bonds. This notation also facilitates country- and sector-specific subsample estimations by conditioning on $D_i^c = 1$ or $D_i^s = 1$, respectively.

Finally, we merge the green bond mid-price series $p_{i,t}$ with the communication and sentiment indices as well as the control variables. The resulting panel dataset features both cross-sectional and temporal dimensions: The entity dimension corresponds to individual green bonds i, while the time dimension corresponds to daily observations t.

Formally, the panel can be written as

$$p_{i,t} = f(CSS_{c,t}^{\text{home}}, CSS_{c,t}^{\text{ECB}}, CSS_{c,t}^{\text{rest}}, Sent_{c,t}^{\text{home}}, Sent_{c,t}^{\text{ECB}}, Sent_{c,t}^{\text{rest}}, y_{c,t}, BAS_{i,t},) \tag{12}$$

4.1 Baseline Regression

We estimate the following pooled panel regression model, in which the daily mid-price level $p_{i,t}$ of green bond i is regressed on our communication and sentiment indicators:

$$\begin{aligned} p_{i,t} \; &= \alpha + \beta_1 \, CSS_{i,t}^{\text{home}} + \beta_2 \, CSS_{i,t}^{\text{ECB}} + \beta_3 \, CSS_{i,t}^{\text{rest}} \\ &\quad + \delta_1 \, Sent_{i,t}^{\text{home}} + \delta_2 \, Sent_{i,t}^{\text{ECB}} + \delta_3 \, Sent_{i,t}^{\text{rest}} \\ &\quad + \theta_1 \left(CSS_{i,t}^{\text{home}} \times Sent_{i,t}^{\text{home}} \right) + \theta_2 \left(CSS_{i,t}^{\text{ECB}} \times Sent_{i,t}^{\text{ECB}} \right) \\ &\quad + \theta_3 \left(CSS_{i,t}^{\text{rest}} \times Sent_{i,t}^{\text{rest}} \right) \\ &\quad + \gamma_1 \, BAS_{i,t} + \gamma_2 \, y_{c(i),t}^{\text{10y}} + \varepsilon_{i,t}. \end{aligned} \tag{13}$$

Here, $p_{i,t}$ denotes the mid-price of green bond i at time t. The variables $CSS_{i,t}^{\text{home}}$, $CSS_{i,t}^{\text{ECB}}$, and $CSS_{i,t}^{\text{rest}}$ capture the intensity of climate-related communication by the domestic central bank, the European Central Bank, and all other euro area central banks, respectively. Analogously, $Sent_{i,t}^{\text{home}}$, $Sent_{i,t}^{\text{ECB}}$, and $Sent_{i,t}^{\text{rest}}$ represent the sentiment indices derived from the FinBERT language model. The interaction terms $CSS \times Sent$ capture whether the impact of climate-related communication depends on its emotional tone.

The control variables $BAS_{i,t}$ and $y_{i,t}^{\text{home}}$ denote the bid-ask-spread of bond i, measuring market liquidity, and the ten-year sovereign bond yield of the issuer's home country $c(i)$, controlling for changes in the general interest-rate environment. The error term $\varepsilon_{i,t}$ captures unobserved factors affecting bond prices.

Since this specification does not include country or sector fixed effects, all observations are treated equally across countries and industries. The model therefore constitutes a pooled regression, providing a baseline estimate of the average effect of central bank communication on green bond prices in the euro area.

We estimate four nested specifications that progressively incorporate different dimensions of the communication variables. Model A includes only the climate speech score indices ($CSS_{i,t}^{\text{home}}$, $CSS_{i,t}^{\text{ECB}}$, and $CSS_{i,t}^{\text{rest}}$) to identify the effect of the intensity of climate-related central bank communication on green bond prices. Model B focuses exclusively on the sentiment indices ($Sent_{i,t}^{\text{home}}$, $Sent_{i,t}^{\text{ECB}}$, and $Sent_{i,t}^{\text{rest}}$) and thereby isolates the effect of tone and emotional framing. Model C combines both sets of indicators, treating communication intensity and sentiment as independent, additive influences on bond prices. Finally, Model D extends this specification by including the interaction terms between CSS and $Sent$, thereby allowing the impact of communication intensity to vary with the sentiment conveyed in the speech.

4.2 Sample Splits

To explore potential heterogeneity in the transmission of central bank communication, we re-estimate the baseline model for country- and sector-specific subsamples. This approach enables us to assess whether the effects of climate-related central bank communication and sentiment vary across national bond markets and industry segments.

For the country-level analysis, we estimate the baseline regression separately for each issuer country c by conditioning on the respective country dummy $D_i^c = 1$. Formally, for all bonds i issued in country c, the model is specified as

$$
\begin{aligned}
p_{i,t}^{(c)} = = \; & \alpha_c + \beta_{1,c}\, CSS_{i,t}^{\text{home}} + \beta_{2,c}\, CSS_{i,t}^{\text{ECB}} + \beta_{3,c}\, CSS_{i,t}^{\text{rest}} \\
& + \delta_{1,c}\, Sent_{i,t}^{\text{home}} + \delta_{2,c}\, Sent_{i,t}^{\text{ECB}} + \delta_{3,c}\, Sent_{i,t}^{\text{rest}} \\
& + \theta_{1,c} \left(CSS_{i,t}^{\text{home}} \times Sent_{i,t}^{\text{home}} \right) + \theta_{2,c} \left(CSS_{i,t}^{\text{ECB}} \times Sent_{i,t}^{\text{ECB}} \right) \\
& + \theta_{3,c} \left(CSS_{i,t}^{\text{rest}} \times Sent_{i,t}^{\text{rest}} \right) \\
& + \gamma_1\, BAS_{i,t} + \gamma_2\, y_{i,t}^{10\text{y}} + \varepsilon_{i,t}^{(c)}.
\end{aligned} \tag{14}
$$

Each regression is estimated as a pooled panel model within the respective subsample, treating all bond issued in the same country as one cross-sectional group. The coefficients $\beta_{k,c}$, $\delta_{k,c}$, and $\theta_{k,c}$ are therefore country-specific, capturing how domestic, ECB, and foreign climate communication affect green bond prices in each national market.

Analogously, to assess heterogeneity across industries, we estimate the same specification for each sector s, conditioning on $D_i^s = 1$. For all bonds i belonging to sector s, the model is specified as follows:

$$
\begin{aligned}
p_{i,t}^{(s)} = = \; & \alpha + \beta_{1,s}\, CSS_{i,t}^{\text{home}} + \beta_{2,s}\, CSS_{i,t}^{\text{ECB}} + \beta_{3,s}\, CSS_{i,t}^{\text{rest}} \\
& + \delta_{1,s}\, Sent_{i,t}^{\text{home}} + \delta_{2,s}\, Sent_{i,t}^{\text{ECB}} + \delta_{3,s}\, Sent_{i,t}^{\text{rest}} \\
& + \theta_{1,s} \left(CSS_{i,t}^{\text{home}} \times Sent_{i,t}^{\text{home}} \right) + \theta_{2,s} \left(CSS_{i,t}^{\text{ECB}} \times Sent_{i,t}^{\text{ECB}} \right) \\
& + \theta_{3,s} \left(CSS_{i,t}^{\text{rest}} \times Sent_{i,t}^{\text{rest}} \right) \\
& + \gamma_1\, BAS_{i,t} + \gamma_2\, y_{i,t}^{10\text{y}} + \varepsilon_{i,t}^{(s)}.
\end{aligned} \tag{15}
$$

Each regression is again estimated as a pooled model within the respective sector subsample. The resulting parameter sets $(\beta_{k,s}, \delta_{k,s}, \theta_{k,s})$ capture whether the effects of communication and sentiment differ systematically across the categories: electric, estate, financial, government, and transport.

Both the country- and the sector-level regressions employ the same estimation method as the baseline model - pooled panel least squares with robust standard errors. The results from these estimations are later compared across groups to assess heterogeneity in the sensitivity of green bond

prices to climate-related central bank communication.

5 Results

Table 10 presents summary statistics for all variables included in the regression analysis. Green bond prices exhibit considerable cross-sectional and temporal variation, with an average level of approximately 91 and a standard deviation of about 20.5. The observed range, from 8.5 to 159.2, reflects substantial heterogeneity across issuers and over time, consistent with the coexistence of both government- and corporate-issued green bonds of varying maturities and credit quality. The average bid-ask spread of 0.69 suggests that most green bonds trade in relatively liquid secondary markets, although the maximum value of 15 indicates that certain instruments experience periods of illiquidity. The mean ten-year government bond yield of 1.23 percent (ranging from -0.84 to 8.15 percent) captures the pronounced decline and subsequent rebound in euro area long-term rates over the sample period.

The communication indices display much smaller magnitudes, as expected given their normalized scale. The mean of the domestic Climate Speech Score (CSS Home) is slightly positive (0.04), while the ECB index is slightly negative (-0.02), suggesting that national central banks have, on average, communicated marginally more intensively about climate issues than the ECB. The "Rest" index, which aggregates speeches from other central banks, is centered close to zero, reflecting the sparse and event-driven nature of climate-related communication in this group.

Sentiment indices range between -1 and +1, with positive means observed across all three groups. Domestic speeches tend to convey the most positive tone (mean of 0.52), followed by the Rest (0.25) and the ECB (0.11), suggesting that national authorities discuss climate-related topics in a relatively optimistic or policy-supportive manner.

The final column reports the results of the unit-root tests based on the ADF-Fisher chi-square with Newey-West automatic bandwith selection and Bartlett kernel. Lag length is determined by the Schwarz Information Criterion (SIC). The unit-root null is rejected at conventional levels for all vari-

ables.

Table 10: Summary statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Unit root test
Green bond price	90.995	93.909	20.506	8.500	159.188	—
Bid–Ask spread	0.692	0.438	0.951	0.085	15.000	0.000
Gov. bond yield (10y)	1.228	0.745	1.322	−0.844	8.153	0.052
CSS Home index	0.040	0.003	0.150	−0.209	0.695	0.000
CSS ECB index	−0.023	−0.046	0.135	−0.313	0.647	0.000
CSS Rest index	0.023	−0.060	0.138	−0.120	0.695	0.000
Sentiment Home index	0.520	1.000	0.830	−1.000	1.000	0.000
Sentiment ECB index	0.110	0.500	0.920	−1.000	1.000	0.000
Sentiment Rest index	0.230	0.500	0.820	−1.000	1.000	0.000

Notes: The table reports descriptive statistics for all variables used in the regression analysis.

5.1 Baseline Regression

Table 11 presents our baseline results.

All four models use the correct prefix for the control variables and consistently show that both, the content and the sentiment of central bank speeches have a significant impact on green bond prices. While Model A and B identify the individual effects, Model C confirms that these effects remain robust when both variables are included simultaneously. Moreover, Model D suggests that interaction of CSS and sentiment is important, indicating that the impact of communication intensity depends on the tone conveyed in the speech.

For the climate speeches, more strongly climate-related speeches delivered domestically tend to lead to an increase in the green bond prices. This is evident from the positive coefficients on the CSS Home index in both Models A and D. In contrast, speeches delivered abroad are associated with a decline in domestic green bond prices. This can be seen on the CSS Rest index for all

Table 11: Baseline Regressions

	Model A	Model B	Model C	Model D
Intercept	108.97^{***}	109.84^{***}	109.92^{***}	109.83^{***}
	(0.12)	(0.11)	(0.12)	(0.12)
CSS Home index	0.74^{*}		0.55	0.85^{*}
	(0.41)		(0.41)	(0.48)
CSS ECB index	0.64		−0.09	0.09
	(0.45)		(0.45)	(0.45)
CSS Rest index	-3.07^{***}		-2.00^{***}	-1.39^{***}
	(0.44)		(0.45)	(0.46)
Sentiment Home index		-2.08^{***}	-2.06^{***}	-2.04^{***}
		(0.07)	(0.07)	(0.07)
Sentiment ECB index		-0.21^{***}	-0.18^{**}	-0.14^{**}
		(0.06)	(0.06)	(0.06)
Sentiment Rest index		-0.47^{***}	-0.48^{***}	-0.37^{***}
		(0.06)	(0.07)	(0.07)
CSS Home × Sentiment Home				−0.52
				(0.49)
CSS ECB × Sentiment ECB				-1.71^{***}
				(0.48)
CSS Rest × Sentiment Rest				-2.37^{***}
				(0.55)
Bid–Ask spread	-0.98^{***}	-0.90^{***}	-0.89^{***}	-0.89^{***}
	(0.06)	(0.06)	(0.06)	(0.06)
Gov. bond yield (10y)	-9.54^{***}	-9.54^{***}	-9.56^{***}	-9.56^{***}
	(0.04)	(0.04)	(0.04)	(0.04)
R^2	0.41	0.42	0.42	0.42
n	72,976	72,976	72,976	72,976

Notes: Coefficients reported in the first line; heteroskedasticity-robust standard errors in parentheses.
*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

three models, as indicated by the negative coefficients on the CSS Rest index across all three models. One potential explanation for this observed decline is that foreign climate speeches may prompt investors to reallocate capital towards countries where climate protection is receiving greater emphasis. Consequently, increased climate-related activity abroad can lead to capital outflows from the domestic green bond market, resulting in reduced demand and lower prices for domestic green bonds.

Regarding the sentiment, all three sentiment indices (Sentiment Home, Sentiment ECB and Sentiment Rest) exhibit a significant negative relationship with green bond prices: more positively framed communication - whether domestic, by the ECB or from foreign actors - tends to trigger price declines. This effect is statistically significant across the three Models B, C and D, with comparable magnitudes. In other words, the more positive the tone of a speech, the more pronounced the negative impact on bond prices.

By combining climate focus with sentiment (Model D), the results reveal significant negative interaction terms, indicating that when a climate-focused speech is delivered in a positive tone, it exerts particularly strong downward pressure on green bond prices. While there is no significant effect for the Home variable, the magnitude of this effect is evident for the CSS ECB x Sentiment ECB and CSS Rest x Sentiment Rest interactions, where the mid price decreases on average by 1.71 and 2.37 Euros. This coefficient can be interpreted in the context of the "climate-related risks" narrative identified by Campiglio et al. (2025). As mentioned above, their study demonstrates that when central bank communication emphasizes climate-related risks - which in our analysis correspond to negative sentiment - markets tend to respond with negative price adjustments, reflecting heightened perceptions of risk and uncertainty. In our framework, where we combine the CSS with sentiment, the results further support the theory that investors interpret high climate content delivered with an optimistic tone as a signal of potential future adjustments to green bond eligibility criteria or taxonomy thresholds.

5.2 Sample Splits

5.2.1 Sample Split by Countries

When the data are split by country (Table 12), the regression results reveal pronounced cross-country heterogeneity in the effect of domestic climate communication on green bond prices. In Belgium, the coefficient for the CSS Home index is 13.9, indicating that climate-related discourse by national policymakers is associated with a very large and statistically significant increase in prices. This finding is consistent with the results from our baseline regression. By contrast, the effect in Germany is negative (–4.9), suggesting that climate communication there is perceived as a signal of potential costs, risks, or policy uncertainty rather than as a stabilizing commitment. Greece (0.94) and the Netherlands (1.73) exhibit more modest but positive effects, implying that markets in these countries price climate discourse favorably, though far less strongly than in Belgium. These findings indicate that investors interpret climate communication through the lens of national context: while in Belgium such rhetoric appears to reinforce credibility and attract ESG-oriented demand, in Germany it may be discounted as costly or redundant. Overall, the results underscore that the market impact of climate speech is not uniform across the euro area, but is mediated by domestic political and institutional conditions.

Turning to the CSS index of the ECB, the results show that ECB climate communication has no statistically significant effect on green bond prices in most countries, consistent with the overall findings. The only exceptions are Germany and Ireland, where the CSS ECB coefficients are positive and significant. This suggests that, while supranational climate discourse by the ECB is generally not priced by financial markets across the euro area, in these two countries it carries informational value that is reflected in bond pricing.

The CSS Rest index is significantly negative in almost all countries, with the strongest effects observed in Ireland (-13.34) and the weakest in Belgium (-0.92). This finding is consistent with our previous results and indicates that climate-related communication by other central banks is generally associated

Table 12: Sample Split – Countries

	BE	DE	FR	GR	IE	IT	NL
Intercept	101.408***	101.461***	108.258***	102.099***	103.884***	116.708***	103.212***
	(0.340)	(0.333)	(0.232)	(0.125)	(0.687)	(0.532)	(0.182)
CSS Home index	13.935***	−4.875***	1.687	0.939***	−5.407	−0.591	1.732***
	(0.840)	(0.588)	(1.393)	(0.329)	(5.196)	(0.467)	(0.412)
CSS ECB index	−0.206	1.662**	−0.303	−0.081	9.700***	−0.149	−0.150
	(0.261)	(0.755)	(0.663)	(0.333)	(2.736)	(0.514)	(0.510)
CSS Rest index	−0.915***	0.957	−2.998***	−0.466	−13.344***	−1.242**	−4.569***
	(0.263)	(0.901)	(0.655)	(0.340)	(2.501)	(0.532)	(0.506)
Sentiment Home index	−3.054***	0.957***	−0.588***	−0.401***	−4.662***	−0.242***	−0.320***
	(0.051)	(0.117)	(0.150)	(0.055)	(0.515)	(0.082)	(0.078)
Sentiment ECB index	−0.215***	−0.123	−0.237***	0.199***	−0.997***	−0.011	−0.150**
	(0.035)	(0.112)	(0.092)	(0.048)	(0.386)	(0.073)	(0.070)
Sentiment Rest index	0.496***	−0.860***	−0.152	0.415***	0.321	0.154*	0.424***
	(0.046)	(0.127)	(0.109)	(0.063)	(0.482)	(0.093)	(0.079)
CSS Home × Sentiment Home	−10.746***	−4.609***	−1.682	−0.111	6.851	0.0265	0.199
	(0.883)	(0.578)	(1.519)	(0.328)	(5.236)	(0.476)	(0.399)
CSS ECB × Sentiment ECB	1.270***	−0.736	−2.321***	0.344	2.185	−0.429	−1.015**
	(0.281)	(0.796)	(0.696)	(0.369)	(2.915)	(0.551)	(0.485)
CSS Rest × Sentiment Rest	−1.571***	−1.351	−3.179***	−1.703***	6.031**	−1.127*	−1.253**
	(0.321)	(1.111)	(0.759)	(0.410)	(3.065)	(0.649)	(0.620)
Bid–Ask spread	8.138***	−4.505***	4.242***	0.912***	−5.964***	−17.288***	5.226***
	(0.683)	(0.517)	(0.115)	(0.093)	(0.175)	(0.909)	(0.253)
Gov. bond yield (10y)	−3.695***	−4.924***	−12.122***	−2.260***	−2.543***	−5.460***	−5.639***
	(0.080)	(0.096)	(0.068)	(0.037)	(0.464)	(0.083)	(0.051)
R^2	0.875	0.410	0.551	0.732	0.778	0.756	0.506
n	2234	6629	39567	1463	1584	2656	18843

Notes: Coefficients in the first line; heteroskedasticity-robust standard errors in parentheses.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

with declining mid prices in euro area bond markets. A plausible explanation is the one already discussed above. The stronger negative response in Ireland compared to Belgium may further reflect heterogeneity in how national markets assess the external relevance of foreign central bank communication, with Irish markets being more sensitive to international monetary signals, while Belgian markets appear more insulated. No significant effects are observed for Germany and Greece.

Our analysis reveals a striking consistency in the effect of domestic speech sentiment on the pricing of green bonds, which is in line with the results of our baseline regression (see Table 3). Across almost all countries in the sample, a more positive tone in political speeches is associated with a statistically significant decline - ranging from -4.66 Euros in Ireland to -0.24 Euros in Italy - in the price of green bonds, suggesting that investors interpret optimism in rhetoric as a potential signal of green-washing, overcompensation, or informational asymmetries. In this context, optimistic language appears to undermine rather than strengthen market confidence, leading to higher risk premia. Germany is the sole exception, where positive sentiment correlates with an increase in prices (by 0.96 Euro), suggesting that optimistic rhetoric is perceived as credible, aligned with concrete policy actions, and thus reinforces investor trust. This divergence underscores the country-specific nature of how political communication is processed by financial markets, with credibility and institutional reputation determining whether positive rhetoric is interpreted as reassurance or as a warning signal.

When considering the sentiment of ECB speeches, across almost all countries, a more positive tone in ECB communication is associated with a statistically significant decline in green bond prices, consistent with the baseline results. Germany and Italy, however, do not exhibit statistically significant effects.

By contrast, the sentiment of speeches delivered by foreign central banks does not yield consistent effects on green bond pricing. In some countries, the prices rise (Belgium, Greece, Netherlands and Italy), while in Germany the prices decline and in France and Ireland there are no statistically significant effects. The absence of a clear relationship suggests that investors either place

less weight on foreign central bank rhetoric when forming expectations in domestic green bond markets, or that any potential influence is overshadowed by country-specific factors and domestic policy signals. This finding further underscores the primacy of national and ECB communication in shaping investor perceptions of green bond risk and valuation.

When accounting for the interaction of the CSS with the Sentiment Index, a particularly striking pattern emerges. Statistically significant values for the Home Index are found only in Belgium and Germany, while for the ECB Index, significant effects are observed exclusively in Belgium, France, and the Netherlands. For the Rest Index, which captures the impact of foreign central banks, statistically significant effects are present in all countries except Germany. Across all countries - except Ireland and, to some extent, Belgium - more positive sentiment in climate-related speeches is generally associated with declining green bond prices. This suggests that optimistic rhetoric in climate communication is interpreted by investors less as a reassuring signal of commitment and more as a potential indication of overstatement or credibility concerns, thereby increasing the perceived risk premium. Ireland and Belgium stand out as the only cases where positive sentiment in climate speeches is linked to higher mid prices, indicating that in these markets, optimistic climate rhetoric is perceived as credible and reinforces investor confidence. This divergence underscores the heterogeneous ways in which financial markets process climate-related political communication, with credibility and institutional context shaping whether positive sentiment strengthens or undermines green bond valuations.

This heterogeneity in market responses must also be considered in light of the underlying data structure. The Rest Index, for example, comprises a substantially larger set of speeches compared to the more limited number available for individual countries (Home Index) or the ECB (ECB Index). While the ECB's limited impact on green bond prices may appear surprising, it reflects its mandate, which does not prioritize climate protection. As a result, ECB communications are less frequent and less emotionally charged than those of national central banks. Notably, the ECB exerts a strong influence on France and on smaller countries such as Belgium, whose central

banks have less global significance. Campiglio et al. (2025) supports this, arguing that central banks' climate communication strategies are shaped by institutional frameworks and epistemic communities rather than direct climate risk exposure.

5.2.2 Sample Split by Sectors

When the results are analyzed at the sectoral level (Table 13), the findings are overall in line with our baseline model.

Domestic climate speeches are highly significant across all sectors and, with the exception of the government sector, lead to rising prices. Climate-related speeches by the ECB are only relevant for the financial and government sectors, where increased climate communication is associated with higher green bond prices. In contrast, speeches from other countries are significant for all industries except the transport sector and generally result in declining bond prices. For the government sector, we observe a statistically significant negative price effect. This is likely due to the fact that government bonds are considered low-risk assets by professional investors and are widely used for hedging strategies. Consequently, any political decision perceived as detrimental to the financial outlook of the issuing government reduces demand, increases risk premiums, and lowers the prices of the respective government bonds.

While the Sentiment Home Index is statistically significant for all sectors except the electric sector and generally leads to declining prices, the sentiment of the ECB Index is significant for all sectors except transport and also results in declining prices. Sentiment from abroad is statistically significant only for the financial and government sectors, where it is associated with rising prices.

Given the combination of CSS and sentiment, significant effects are observed primarily for the home index, while the ECB index and the foreign index show hardly any significant impact across sectors. The CSS x Sentiment Home Index is associated with declining green bond prices in the electric, estate, and transport sectors, but leads to rising prices in the gov-

Table 13: Sample Split – Sectors

	electric	estate	financial	government	transport
Intercept	104.309***	117.322***	105.799***	104.276***	108.633***
	(0.227)	(0.598)	(0.119)	(0.126)	(0.221)
CSS Home index	3.886***	5.100***	3.491***	−0.839***	8.013***
	(0.555)	(0.834)	(0.480)	(0.246)	(0.918)
CSS ECB index	0.657	1.545	2.057***	1.137***	−0.693
	(0.683)	(1.052)	(0.469)	(0.301)	(0.647)
CSS Rest index	−2.350***	−3.023**	−5.356***	−2.555***	−0.854
	(0.791)	(1.281)	(0.486)	(0.329)	(0.644)
Sentiment Home index	0.080	0.675***	−1.159***	−0.381***	−2.092***
	(0.099)	(0.161)	(0.074)	(0.053)	(0.133)
Sentiment ECB index	−0.210**	−0.818***	−0.246***	−0.229***	0.015
	(0.099)	(0.154)	(0.066)	(0.044)	(0.089)
Sentiment Rest index	0.117	−0.244	0.296***	0.130**	−0.009
	(0.113)	(0.183)	(0.081)	(0.055)	(0.107)
CSS Home × Sentiment Home	−6.359***	−7.011***	0.244	1.674***	−8.073***
	(0.546)	(0.802)	(0.478)	(0.244)	(0.980)
CSS ECB × Sentiment ECB	−1.124	0.722	−0.468	−0.232	−2.138***
	(0.726)	(1.134)	(0.502)	(0.324)	(0.680)
CSS Rest × Sentiment Rest	−3.354***	−1.931	0.284	0.272	−3.390***
	(0.928)	(1.564)	(0.587)	(0.413)	(0.750)
Bid–Ask spread	−4.257***	−37.198***	−5.607***	1.842***	4.107***
	(0.275)	(1.178)	(0.039)	(0.110)	(0.110)
Gov. bond yield (10y)	−3.114***	−4.864***	−5.190***	−12.736***	−11.185***
	(0.069)	(0.114)	(0.048)	(0.045)	(0.066)
R^2	0.229	0.629	0.707	0.993	0.514
n	10419	2692	1720	1582	42408

Notes: Coefficients reported in the first line; heteroskedasticity-robust standard errors in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ernment sector. As previously discussed in relation to the CSS Rest Index, this increase can be attributed to the importance of government bonds for investors and the relevance of potential political implications.

Similar to the results from Vissing-Jorgensen (2019), the prices are more driven by the informal communication by the central banks than by the formal one from ECB.

5.3 Robustness Checks

To assess the robustness of our baseline results, we re-estimate the specification from model D using two alternative panel structures. First, we estimate a bond-fixed effects (FE) model, which absorbs all time-invariant heterogeneity across individual green bonds - such as differences in coupon structure, liquidity, or issuer reputation. Second, we estimate a random effects (RE) model based on the Swamy-Arora variance component estimator, which assumes that unobserved bond heterogeneity is uncorrelated with the regressors. Both specifications employ the same set of variables and cover the same time period as the pooled baseline model.

The results reported in Table 14 demonstrate a high degree of robustness across specifications. The coefficients on the climate communication variables and their sentiment counterparts remain stable in magnitude, sign, and statistical significance. In particular, the negative and significant effects of the CSS Rest indices and the strongly negative sentiment coefficients persist across all models, confirming that both the direction and intensity of central bank communication exert a measurable influence on green bond prices.

The interaction between domestic climate speech intensity and sentiment ($CSS_{\text{home}} \times Sent_{\text{home}}$) becomes positive and highly significant in both the FE and RE models, suggesting that, within bonds, a more positive tone reinforces the price effect of domestic climate communication. By contrast, the interaction term ($CSS_{\text{rest}} \times Sent_{\text{rest}}$) remains negative and significant, indicating that optimistic climate rhetoric from foreign central banks continues to depress green bond valuation.

Table 14: Baseline vs. Bond Fixed Effects and Random Effects

	Model D (Pooled)	FE (Bond FE)	RE (Random effects)
Intercept	109.832^{***}	107.971^{***}	109.421^{***}
	(0.122)	(0.086)	(1.295)
CSS Home index	0.852^{*}	-0.739^{**}	-0.738^{**}
	(0.481)	(0.306)	(0.306)
CSS ECB index	0.085	1.200^{***}	1.199^{***}
	(0.450)	(0.279)	(0.279)
CSS Rest index	-1.387^{***}	-0.821^{***}	-0.821^{***}
	(0.464)	(0.288)	(0.288)
Sentiment Home index	-2.041^{***}	-1.160^{***}	-1.161^{***}
	(0.072)	(0.050)	(0.050)
Sentiment ECB index	-0.141^{**}	-0.233^{***}	-0.233^{***}
	(0.064)	(0.039)	(0.039)
Sentiment Rest index	-0.367^{***}	-0.220^{***}	-0.220^{***}
	(0.074)	(0.046)	(0.046)
CSS Home × Sentiment Home	−0.522	1.906^{***}	1.905^{***}
	(0.493)	(0.308)	(0.308)
CSS ECB × Sentiment ECB	-1.709^{***}	0.020	0.017
	(0.478)	(0.295)	(0.295)
CSS Rest × Sentiment Rest	-2.370^{***}	-2.229^{***}	-2.228^{***}
	(0.548)	(0.338)	(0.338)
Bid–Ask spread	-0.887^{***}	2.714^{***}	2.709^{***}
	(0.062)	(0.056)	(0.056)
Gov. bond yield (10y)	-9.557^{***}	-10.128^{***}	-10.127^{***}
	(0.043)	(0.030)	(0.030)
R^2	0.422	0.780	0.650
n	72976	72976	72976

Notes: Coefficients in the first line; standard errors in parentheses.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
FE model includes green-bond fixed effects; RE model estimated via panel EGLS with cross-section random effects (Swamy–Arora).

The inclusion of bond fixed effects substantially increases the explanatory power of the model ($R^2 = 0.78$), indicating that persistent bond-specific characteristics account for a large share of overall price variation. The random-effects specification ($R^2 = 0.65$) yields nearly identical coefficient estimates, confirming that the main findings are not driven by unobserved heterogeneity.

Overall, the robustness checks confirm that the observed link between climate-related central bank communication and green bond prices is not an artifact of model specification. The significance, direction, and relative magnitudes of the key coefficients remain stable across pooled, fixed-, and random-effects estimations, reinforcing the conclusion that both the content and tone of monetary authorities' climate communication have economically meaningful effects on green bond valuations.

6 Conclusions

The results demonstrate a statistically significant relationship between central bank communication and the pricing of green bonds, with both the content and sentiment of communication playing a crucial role. More frequent climate-related speeches by the domestic central bank are associated with rising bond prices, whereas climate-related speeches by foreign central banks tend to result in declining bond prices. Notably, ECB speeches appear to have only a limited impact on green bond prices. While these effects are statistically significant, they do not apply equally or to the same extent across all countries. Germany stands out due to its high number of speeches and strong focus on climate protection, exemplified by Bundesbank leadership roles such as Sabine Mauderer chairing the NGFS (Deutsche Bundesbank, 2025). In contrast, Ireland's alignment with the Anglo-Saxon sphere, rather than continental Europe, helps explain its outlier status.

In summary, central bank communication has a clear potential to influence the pricing of green bonds. Central bank speeches provide information that is relevant for green bond valuation and should be closely monitored by professional investors and the academic community. The impact of foreign central bank speeches and their alignment with a unified direction across

Europe also plays a significant role in shaping outcomes. However, neither a high volume of speeches nor positive sentiment alone fully explains the evolution of green bond prices, as other dynamics undoubtedly contribute to price formation. Therefore, it is advisable that central banks within the euro area - including both national central banks and the ECB - to pursue a coordinated and unified communication strategy on green finance. Speaking with one voice and aligning their messaging can help minimize market fragmentation and reduce the risk of divergent interpretations across member states. This is particularly relevant for the ECB, whose statements, although less frequent on the topic of green bonds compared to some national central banks, carry significant weight not only within the euro area but also in broader European and global financial markets. Accordingly, market participants should pay close attention to the ECB's communications, as their content -despite being limited in volume - often signals important policy directions. In light of these considerations, it is recommended that financial market participants systematically monitor and analyze the coordinated communication efforts of both the ECB and national central banks. Doing so will enhance their ability to anticipate market movements and make informed investment decisions in the green bond segment.

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