Don't Lead Me This Way: Central Bank Guidance at the Age of Climate Change

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Abstract

Using Natural Language Processing under the form of topic modelling, we are able to extract a specific topic labeled "Climate Change" from ECB communication on the period 1997-2021. We found an exponential increase of the presence of this topic in ECB communication since mid-2018. The analysis of the terms employed in ECB speeches on this topic provides evidence that the ECB talks about climate change as a source of risk for financial markets, leading financial actors to expect a potential regulatory risk from the ECB. Second, we use our findings from this first study and show that an increase in ECB communication about climate change leads to an overall increase in 168 North-American firms' probability of default proxied by their Credit Default Swaps spread returns. Moreover, we provide evidence of a nonlinear effect of ECB communication about climate change on CDS spread returns, with significant and negative estimated coefficients in the short-term, non-significant ones in medium term and strongly significant and positive estimated coefficients on the long term. Finally, our results suggest that the market recognizes which sectors are better positioned for a transition to a low-carbon economy.

Keywords: Climate Change, Central Banking, ECB, Monetary Policy, Credit Risk, Regulation, Credit Default Swap.
JEL Classification: E52, E58, G28, G32, Q54

1 Introduction

Since the adoption of the Paris Agreement in 2015, climate change has been extensively acknowledged worldwide as a cause of perturbations for our economic structure, and a cause of disruption of our financial system. The increasing number of memberships of the Network for Greening the Financial System, from 8 in December 2017 to 121 in October 2022, brings evidence on the fact that central banks take climate change as an increasing threat that should be kept under surveillance[1]

Climate change is not traditionally part of central banks' mandate of price and financial stability. Even if an increasing number of studies find convincing evidence about the link between climate change, the financial system and the real economy, understanding the interconnections between all these angles can still be improved, notably with new and more precise data to design monetary and prudential tools (Campiglio et al., 2018; Chenet et al., 2021; Weitzman, 2009). But far from ignoring it, central banks have started to communicate about climate change.

Central bank communication has been proven to be an effective monetary tool to guide markets' expectations on the future path of overnight interest rate[2]. A flourishing empirical literature has demonstrated the effectiveness of the use of *forward-guidance* as an unconventional tool of monetary policy since the financial crisis of 2007-2008 (Swanson, 2021a; Ehrmann & Fratzscher, 2007). But not only restricted to this particular objective, central banks also disclose their overall objectives and strategies, and share their views on the economic outlook (Haldane & McMahon, 2018; Kryvtsov & Petersen, 2021). In order to be the most effective possible and reduce noise on financial markets, central bank communication must be credible (Bholat et al., 2015). The same credibility has to apply to climate change narrative (Hansen, 2022).

We investigate whether the European Central Bank communicates about climate change and how their perception of climate change will affect the behaviors of financial markets actors. In the first part of this paper, we use an AI-algorithm for natural language processing (NLP) to identify different topics that the ECB communicates on, and their frequency. Our database runs from January 1997 to December 2021 and contains 2,430 speeches given by ECB Executive Board Members during this time period. Our topic-modelling algorithm unveils that 60 topics can be identified. Among them, one in particular can be labeled "Climate Change" and is exponentially more frequent in ECB's speeches since mid-2018. Inside of each topic, we managed to extract the 15 most frequent words. For the topic labeled "Climate Change", we found that the five words most frequently used in ECB speeches' are "risk", "climate", "change", "transition" and "green".

[1]For example, Dikau and Volz (2021) highlight significant differences in how climate objectives do and do not fit within central banks mandates across different countries.

[2]See, for example, Blinder et al. (2008) for an early survey of the literature

Our contribution is threefold: first, to the best of our knowledge, we are the first to use new machine learning topic modelling methodology to analyze and target ECB's communication. We show that the ECB is placing increasing emphasis on climate change in its communication. Finally, when talking about climate change, the ECB refers to it as a "risk" that could affect the stability of the financial system. Therefore, the ECB does not only want to impact financial markets' expectations, but it also tries to ensure financial resilience by nurturing the idea that financial actors must be prepared to face the implementation of restrictive regulation as soon as we will be able to have enough knowledge and data on the impact of climate change on the economy.

This leads us to the second part of our study: how ECB's perception of climate change affects financial actors' behaviors. With the results of our textual analysis, we are able to extract a time series from the frequency of the topic "Climate Change" in ECB's speeches. We then make the assumption that ECB's communication on climate change has an impact on credit risk of firms in some industries. Indeed, we try to understand if the ECB's perception of climate change as a risk has an impact on the probability of default of certain types of firms. To do that, we proxied the probability of default by the variation of the Credit Default Swaps spreads.

CDS spreads are market-based indicators of a firm's perceived riskiness and confidence in their future fundamentals. Alongside with corporate bonds, they are traditionally used in the financial literature on credit risk because they present several advantages. First, because they are traded on standardized terms, they are more reactive to new information arriving on the market. Then, they are more liquid than corporate bonds. Finally, because they have different maturities up to 30 years, they enable us to study the forward-looking considerations of lenders. In our case, we investigate if ECB's communication is a determinant of CDS spreads. We chose to look at CDS of 168 firms, distributed over 10 sectors, that trade CDS at 5, 10 and 30 years. Using CDS spreads allows us to measure how the "greening" of ECB's communication affects investors' expectations of the probability of default of different industries, at different time horizons.

We follow Blasberg et al. (2021) in the use of a quantile regression approach (QR). QR allows us to (i) provide a more complete description of how ECB's communication on climate change is linked to the entire conditional distribution of CDS spread returns, and (ii) to capture the marginal impact of ECB's communication above and beyond known determinants (Han & Zhou, 2015; Hull et al., 2004). Furthermore, QR methodology also presents the advantage of mitigating empirical problems frequently encountered in the CDS literature (e.g. non-normality and the presence of outliers), that could also be present in our data.

Our results show a positive and significant impact of ECB's communication on the variation of CDS spreads, all sectors included, with more significant results for 5-year CDS spreads. We find that the effect of ECB's communication on climate change is significantly amplified at the tails of the credit spread distribution. We further investigate on a sectorial level. The results highlight potential nonlinear effects of the communication of the ECB on the topic of climate change on CDS spread returns. As such, results for short-term maturity (5-year maturity) are significant and negative for firms across all sectors. This suggests that in the short term, (i) market actors seem to have integrated a potential implementation of a regulation coming from the ECB to mitigate the effects of climate change on financial markets, and (ii) firms are already capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation. Nevertheless, in the medium term, (10-year maturity), all the estimated coefficients become non-significant. This confirms that in the medium term, financial actors' are uncertain about the implementation of a new regulation coming from the ECB to mitigate the effects of climate change on financial markets. Finally, in the long-term (30-year maturity), our coefficients estimates of the interaction terms of the sector panel quantile regression become positive and highly significant. CDS market's participants expect a higher probability of default for firms across all sectors with the increase of ECB's communication about climate change.

Overall, we highlight how ECB's communication can impact investors' expectation of the probability of default of different firms at different time horizons. Our findings are particularly relevant on the regulation of climate risk.

The rest of the paper is organized as follows. Section 2 provides an overview of the different strand of the literature this paper is related to, by underlying the added value of our approach. Section 3 presents our first contribution to the literature: the study of ECB's speeches using Natural Language Processing. In this section, we detail our methodology, data and results. In Section 4 we use the results from Section 3 to study the impacts of ECB's communication about climate change on firms' credit risk (proxied by CDS spread returns). Then, we discuss our empirical results in Section 5. Finally, Section 6 concludes.

2 Literature Review

Our paper contributes to several strands of the literature that we summarize therein. First, we measure climate transition risk (CTR) by the means of textual analysis. Second, we take into account communication by Central Banks, in particular the European Central Bank speeches. Our first contribution to the literature is the construction of a new measure of climate transition risk proxied by central bank communication. Finally, we consider the impact of Central Bank communication as a proxy of CTR on credit risk, measured by Credit Default Swaps, a relationship which has not been investigated so far.

2.1 Climate Transition Risk Measurements

Adjustments in regulations, technology, and consumer attitudes aimed at adapting economies to a low carbon setup entails CTR for cash flows that may impair the debt repayment capacity of firms and thus increase their credit risk. Exposure evaluates to what extent carbon risks are materialized in the firm's operations, products, services, and supply chain, which largely depend on the firm's business sector. CTR is mostly measured by the pricing of carbon risk. Firms' exposure to carbon risk is computed by using emission intensity data: high-emitting firms may incur greater costs from changes in policy –through emissions abatement and the adoption of new technologies and product changes in response to changes in consumer preferences.

Multiple proxies for CTR are used in the literature. The most common ones are portfolios based on information on firms' CO2 emissions (Alessi et al., 2021; Blasberg et al., 2021; Gourdel & Sydow, 2022), stranded asset portfolios (H. Jung et al., 2021), fund flows (Briere & Ramelli, 2022), green portfolio factors (Pástor et al., 2021; Pástor et al., 2022), and Sutainalytics Carbon Risk Index (Ugolini et al., 2023). CTR has been documented to be a relevant factor in private and institutional investor portfolio decisions (Krueger, Sautner, & Starks, 2020; Reboredo & Otero, 2021), as well as in the pricing of stocks and bonds (Ilhan, Sautner, & Vilkov, 2021; Bolton & Kacperczyk, 2020; Monasterolo & de Angelis, 2020; Painter, 2020; Reboredo & Ugolini, 2022). Our viewpoint is to broaden the scope of climate transition risk as embedded in communication.

2.2 ECB's communication as a proxy to measure CTR

Engle et al. (2020) is the first paper to suggest the link between textual analysis on climate change and financial markets. The authors use The Wall Street Journal news to measure the degree of attention to climate change and then they construct portfolios whose short-term returns hedge news about climate change over the holding period. By hedging, period by period, the innovations in news about long-run climate change, an investor can ultimately hedge long-run exposure to climate risk. They first extract a climate news series from textual analysis of news sources and then use tools from standard asset pricing theory and construct portfolios that can successfully hedge climate news.

Since the seminal paper by Engle et al. (2020), a flourishing literature uses textual analysis to measure the link between climate change and financial markets. For example, both Bessec and Fouquau (2022) and El Ouadghiri et al. (2021) have worked on index of professional communication of the Wall Street Journal on financial markets. Textual analysis from newspapers, while revealing, may give a bias toward short-term horizon, whereas Central Banks communication is likely to pave the way toward future regulations. We thus proxy climate transition risk by the textual analysis of Central Banks communication speeches. Central Banks monetary policy can promote sound strategies for quantifying long term impacts of exposure to climate change uncertainty. The underlying idea is that uncertainty in policy responses to climate change and short-term vulnerabilities are likely to trigger Central Banks intervention. Official communication on climate change is the first step toward that direction.

Since the seminal work of Morris and Shin (2002), a vast branch of the macro-financial literature has shown that central bank communication is twofold: first, central banks guide expectations; and second, central bank communication is used as a focal point, and thus as a coordination device for the beliefs of financial market participants. Central Bank communication on general economic policies has already been analyzed. Just to cite some recent contributions, Cross and Greene (2020) uses simple textual analysis to study "policy agenda". D'Orazio and Popoyan (2019) construct textual indexes in order to build a dataset on green macroprudential regulation of central bank on OECD and non-OECD area. Bennani et al. (2020) use probit modeling to provide evidence that communication is a tool to manage financial markets' expectations, in particular after a financial crisis. This might be the case as Central Banks communication has stronger impact on financial markets in bad times than in good ones (Gardner et al., 2022).

ECB is one of the most active banks that strategically use communication. Feldkircher et al. (2021) use a structural topic model to show that ECB and national central banks communicate more and more often on "out of the box" contents, beside their core mandate. Beside the general use of communication, ECB is committed to a green policy. On the bank web page, one can read: "An orderly transition to a green economy would, in the long run, reduce climate-related risks for the entire economy and financial system, as well as for the inflation outlook and the assets on the Eurosystem balance sheet. As a result, it would contribute to price and financial stability in the long run. In line with the EU Treaty, the ECB has the obligation, within our mandate and without prejudice to our primary objective of price stability, to support general economic policies in the EU. In this way, we contribute to the transition to a carbon-neutral economy and to protecting the environment".

A few papers have analyzed central bank policies in the green transition. Dikau and Volz (2021) present a qualitative analysis of sustainability mandates, whereas other contributions (Campiglio et al., 2018; Chenet et al., 2021) discuss the reason why banks should include green policy to increase financial stability. Regarding in particular central banks communication on climate change, Arseneau et al. (2022) is the most recent and meaningful contribution, close to ours. The use of single topic modeling techniques allows them to make a textual analysis of large corpus of central banks over 17,000 speeches to identify those related to climate change. They provide evidence on the fact that central banks identify climate change as a potential risks to the financial system, but they tend to use speculative language (that is transmitting the idea of risk and uncertainty) more frequently when talking about climate change relative to other topics. Interestingly, the ECB displays the highest number of climate-related speeches over the entire sample. However, this paper identifies the characteristics of central banks communication on climate change adaptation and mitigation, without exploring or quantifying the impacts on economic variables, as we do.

2.3 CTR Impacts: From Equity to Credit

Although the literature has extensively documented the pricing of the carbon risk in the equity (equity option) market, generally finding that higher carbon emission is associated with stock return premium (Bolton & Kacperczyk, 2020) and higher deep out-of-money put option prices (Ilhan et al., 2021). However, it is still unclear how credit risk across firms may be impacted according to their vulnerability to climate transition, yet this information is crucial as firms with greater exposure and poorer management of CTR *should ceteris paribus* exhibit greater credit risk.

Credit Risks Measurements The relationship between climate/carbon risks and credit risk has not been fully addressed. Therefore, this question attracts attention. This literature is still at its infancy, but it is growing everyday. A first set of papers suggest that firms with high carbon emissions tend to issue bonds with higher yield spreads and worse credit ratings (Seltzer et al., 2022 and Zhan et al., 2023). Others show that bonds of more carbon-intensive firms earn lower returns, suggesting investors' underreaction to carbon risk (Duan et al., 2021). Capasso et al. (2020) provide evidence on the fact that distance-to-default is negatively associated with a firm's emissions. Kleimeier and Viehs (2018) and Vozian (2022) show that a firm's CO2 emissions are negatively related to the cost of bank loans. Ilhan et al. (2021), prove that firms with higher emissions experience greater downside risk. Finally, Carbone et al. (2021) conclude that firms with higher emissions experience worse credit risk estimates.

CDS as a Measure of Credit Risk Credit Default Swaps (CDS) protect against the risk of credit default: buyers pay a premium (CDS spread) to obtain insurance against default. The price of this financial instrument therefore reflects the market assessment of a firm's credit risk. From variations in this assessment across time scales we can obtain spreads for different time horizons for the same borrower. CDS contracts are standardized, traded in liquid markets, and very sensitive to new information (Henricot & Piquard, 2022). Liquidity has increased as from the Paris Agreement. Those features together make CDS as an interesting measure of credit risk.

There is a recent yet growing carbon/climate literature using CDS as a measure of credit risk. Blasberg et al. (2021) describe a carbon risk factor that is computed as the difference between the median values of CDS spreads of firms with low and high emissions, showing that this factor affects the CDS spreads of European and US firms. Using text analysis of climate risks, Kölbel et al. (2020) build proxies for both climate transition and physical risks, documenting that disclosure of transition risks increases firms' CDS spreads, while the opposite occurs for physical risks. Ugolini et al. (2023) provide evidence on the asymmetric effects of the CTR factor on CDS, reporting significant economic and asymmetric effects. On a more "ESG" twist, Duong et al. (2022), analyzing firm-level carbon risk management association with a firm's CDS spreads, find that carbon management actions substantially reduce CDS spreads. Barth et al. (2022) find that improved ESG ratings reduce firm credit risk as reflected in CDS spreads.

2.4 Our Approach

All in all, our overall contribution is to test whether Climate Transition Risk as communicated by the ECB has an impact on the market perception of the default probability, measured by CDS spreads. we therefore test explicitly on of the underlying assumptions suggested by Blasberg et al. (2021):*"When policy events trigger a rise in carbon risk (e.g. expectation of a tighter future regulatory framework), the demand for protection of more (less) exposed firms increases (decreases), resulting in a widening of the wedge. Conversely, if the market expects a loosening of the regulatory framework, there is a narrowing of the wedge (or possibly even a negative wedge)"*. Notice that in our perspective the ECB speeches represent the guidance for investors seeking insurance against CTR of firms in international markets, under the implicit assumption that there are spillovers in CB communication worldwide (Armelius et al., 2020).

3 From Words to Data: A Text-Mining Approach

This section presents our measure of climate-related communication as a proxy for climate transition risk based on ECB Board Members speeches database. In this section, we first report our methodological framework, then we describe our sample of ECB's speeches. Last, we present our results.

3.1 Correlated Topic Model

Topic modeling methods are a popular analytic tool for evaluating data. Numerous methods of topic modeling have been developed which consider many kinds of relationships and restrictions within datasets (Vayansky & Kumar, 2020). Although current topic modeling approaches perform significantly better than early algorithms, they still require optimization and tuning to provide reliable results.

Following this reasoning, a document can be regarded as a unit matrix represented by $W = (W^1, W^2, ..., W^N)$ where W^i represents the i^{th} word in the sequence and N defining the number of words within the document. A corpus is thus represented by $D = (W^1, W^2, ..., W^M)$ or $D = (D^1, D^2, ..., D^M)$ in which D^n is equivalent to W^n and signifies the n^{th} document in the corpus and M defines the total number of documents within the corpus. Topics are represented by different probabilistic or stochastic distributions depending on the method being used, and in some cases can also represent distribution over other topics as well.

We have used the Correlated Topic Model (CTM) by Blei and Lafferty (2007). It is a suitable approach for most any data and would work well with sets which are expected to have strongly correlating topics, as in Central Banks speeches. CTM uses topic correlation to support its prediction by inferring that words from related topics may also be likely within the document. The topic mixtures in CTM are sampled from a logistic normal distribution which transforms a multivariate normal random variable on a simplex and through a covariance matrix of the normal distribution allows for an overall arrangement among the variance between the distribution elements.

3.2 Data

Our study period runs from January 1997 to December 2021. We collected manually from the ECB website[3] all speeches texts given in English by ECB Executive Board members during this time period. In order to have unbiased results when using Latent Dirichlet Allocation, we removed the followings from our sample of texts: surnames and first names, names of countries, cities and regions, nationalities, months and days, footnotes, greetings, acronyms as well as special characters. On days that contains more than one speech, texts are concatenated. We are finally left with a database containing 2,430 speeches delivered by ECB Executive Board Members from February 7th, 1997 to December 10th, 2021.

[3] `https://www.ecb.europa.eu/press/key/date/html/index.en.html`

3.3 Results

3.3.1 Finding the optimal number of topics

Finding the optimal number of topics is at the core of topic modeling tools. A recent work by Zhao et al. (2015) proposes a perplexity-based approach for evaluating topic models where the Rate of Perplexity Change (RPC) is calculated over iterations, and the turning point of this value is used to select for the best fitting number of topics. Perplexity is calculated by splitting a dataset into two parts—a training set and a test set. The idea is to train a topic model using the training set and then test the model on a test set that contains previously unseen documents (i.e. held-out documents).

Coherence statistics, held-out likelihood or likelihood, semantic coherence and exclusivity are the four measures that are used to find the optimal number of topics. When the first two of them give a good understanding of the model fit, the last two ones focus on quality of the topics.

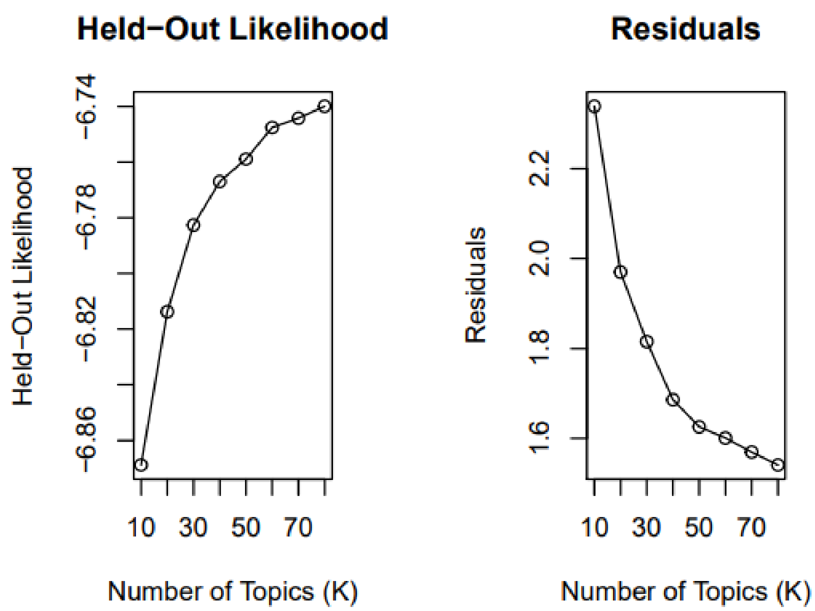

Figure 1: Held-Out Likelihood and Residuals of Our Database of ECB Speeches

Figure 1 illustrates held-out likelihood and residuals for our database of ECB speeches. The optimal number of topics contained in our database should satisfy the condition of having the highest held-out likelihood and the lowest residuals. The held-out likelihood is highest between 60 and 80, and the residuals are lowest around 70. Therefore, we pick 70 as the optimal number of topics in our database.

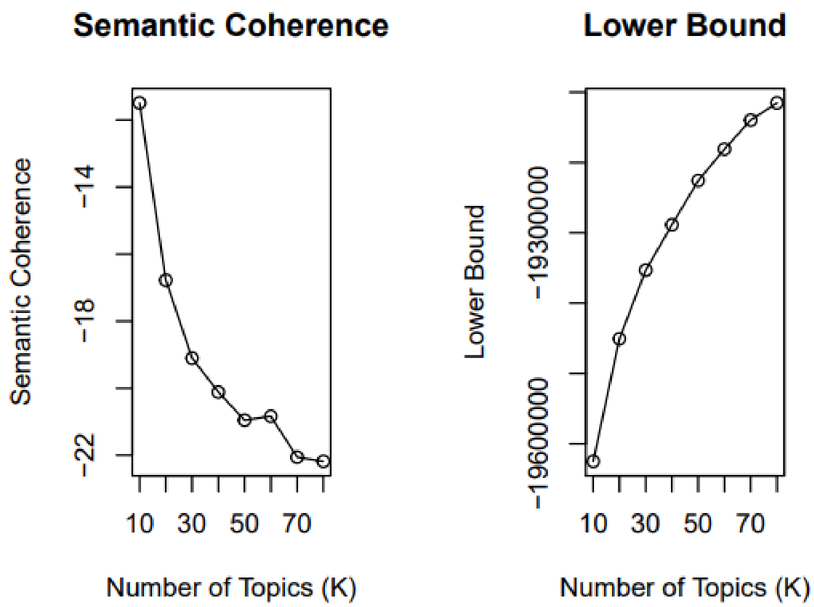

Figure 2: Semantic Coherence and Lower Bound of Our Database of ECB's Speeches

We verified our choice of 70 topics as the optimal number of topics in our database by studying semantic coherence. Semantic coherence is maximized when the most probable words in a given topic frequently co-occur together, and it's a metric that correlates well with human judgment of topic quality. As shown in Figure 2, semantic coherence is maximized for 70 topics.

Having high semantic coherence is relatively easy if there are a few topics dominated by very common words. Therefore, one wants to look at both semantic coherence and exclusivity of words to topics. Exclusivity, such as semantic coherence, focus on the quality of the topics. If words with high probability under topic i have low probabilities under other topics, then we say that topic i is exclusive. A topic that is both cohesive and exclusive is more likely to be semantically useful. Figure 3 confirms our choice of 70 as our optimal number of topics. For this number of topics, exclusivity and semantic coherence are the highest.

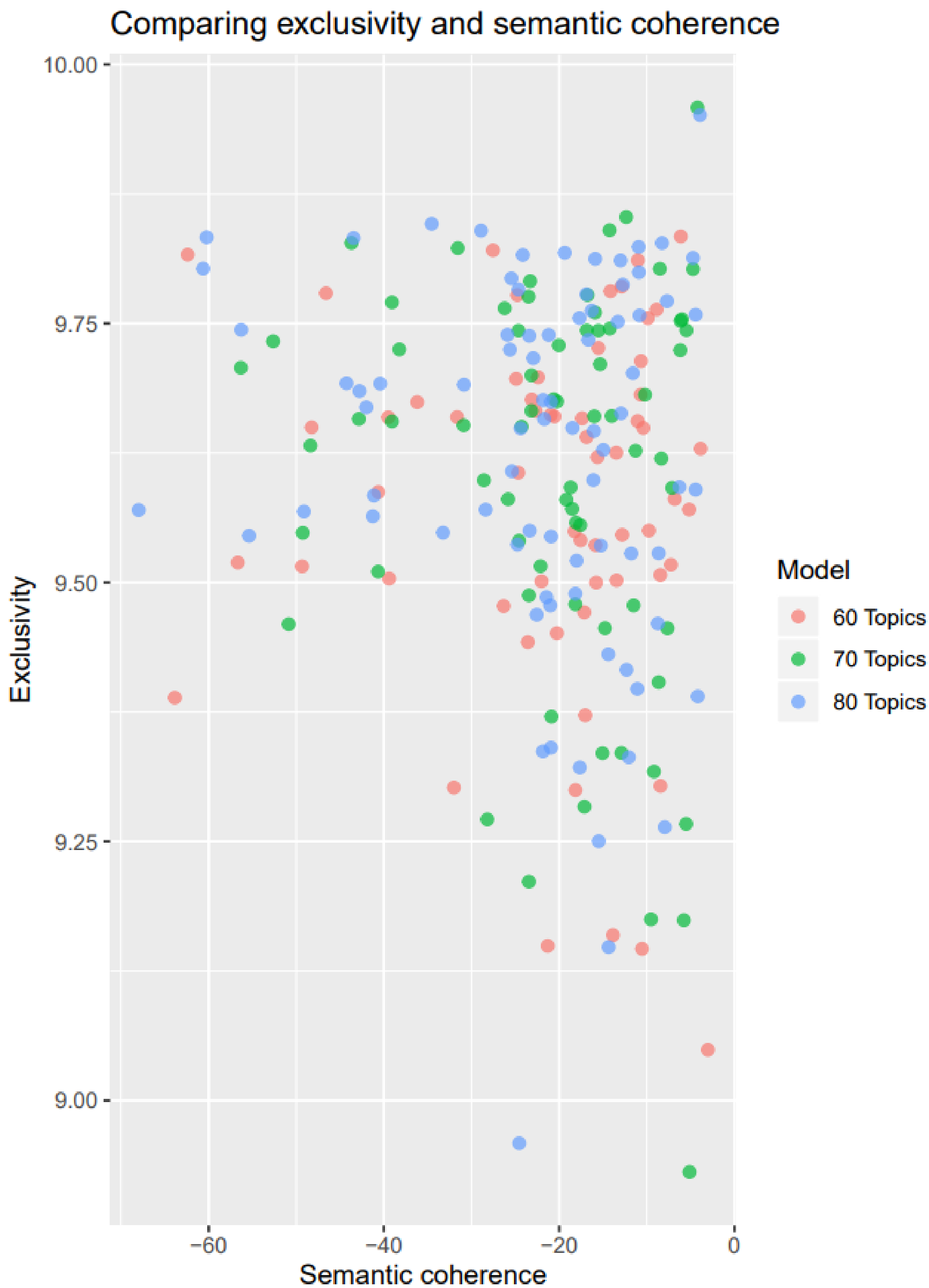

Figure 3: Comparing Exclusivity and Semantic Coherence

We then focus on the most frequently used 10 words inside each topic to order the topics by order of prevalence. Inside of each topic, the most frequent 5 bi-grams gives us the potential label of the topic. We found that one detected topic is labeled by the algorithm as "Climate Change", "Climate Risk", "Green Bonds", "Climate-Related Risk" and "Strategic Review". Our model provides evidence on the fact that the ECB talks enough about climate change to be detectable as a specific and distinct topic in its communication.

3.3.2 Focus on the topic labeled "Climate Change"

Figure 4 presents the proportion of the topic labeled "Climate Change" in ECB speeches, expressed as the percentage of each speech. As shown in Figure 4, we observe an exponential pattern for the relative frequence of the topic "Climate Change" in ECB speeches since the mid-2018 to the end of 2021. For the period 2013-2018, we observe nearly 0% of ECB speeches dedicated to climate change. A peak shows up, from 0% to 0.4%, in mid-2018. Since then, this topic is more and more frequent in ECB speeches, reaching 0.9% as its highest value, at the end of 2021. Overall, climate change is gaining more and more attention in ECB speeches.

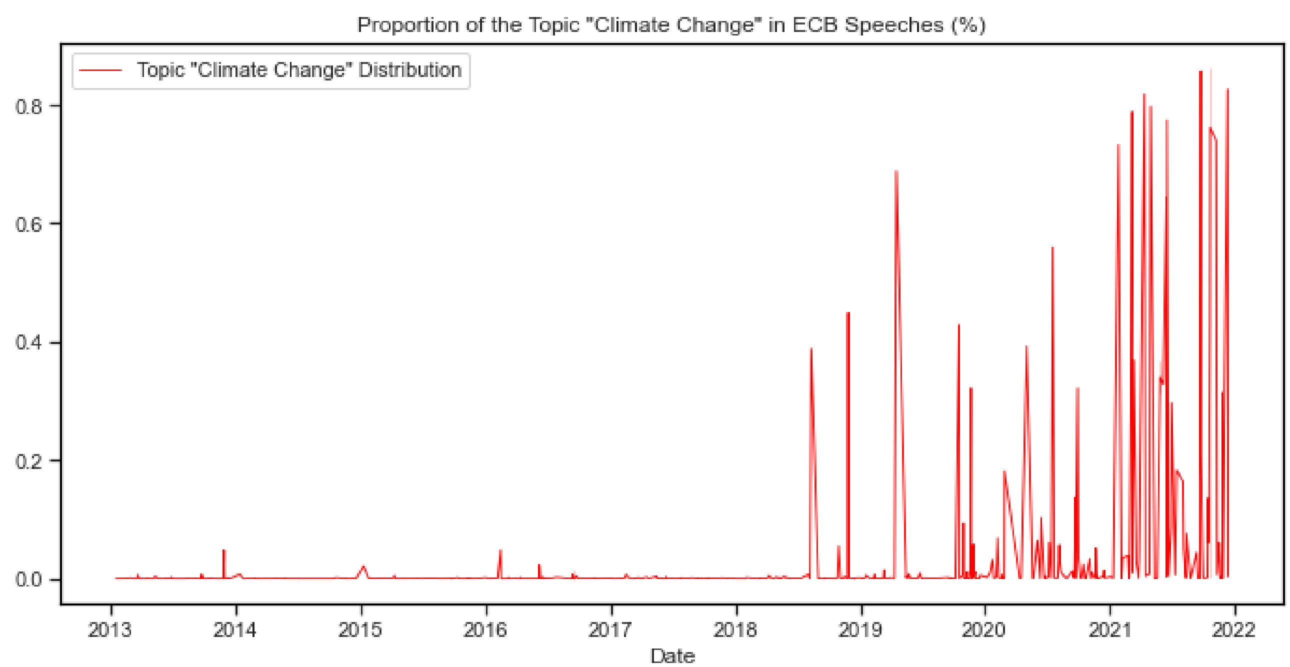

Figure 4: Proportion of the Topic "Climate Change" in ECB Speeches (%)

Figure 5 presents the 100 words most frequently used in ECB speeches in the topic that our model labeled "Climate Change". This word cloud is constructed using the probability of appearance of words in the topic labeled "Climate Change". The size of a word corresponds to the frequency of appearance in ECB speeches in this given topic. Therefore, more a word is used, the highest is the probability of its affiliations to a given topic, and the bigger is its size in Figure 5.

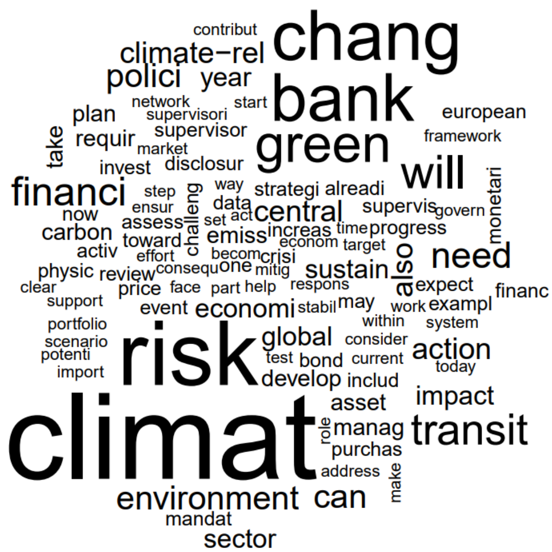

Figure 5: Word Cloud of the 100 Most Frequently Used Words in ECB Speeches in the Topic Labeled "Climate Change"

As shown by Figure 5, the most frequent words used (by order of prevalence inside the topic) are "climate", "risk", "change", "bank", "green", "will", "transition", "financial", "need" and "can". Therefore, ECB perceives climate change as a risk for the financial sector and more precisely for banks. Their use of verb at future tense also provide evidence that the ECB starts to prepare financial actors for the potential introduction of regulations on their behalf or on the behalf of governments.

In the rest of this paper, in order to match our topic variable with our CDS database, we reduce our time period to 2013-2021. Therefore, our empirical analysis in part 4 will be done with the subset of 740 speeches' dates from January 12th, 2013 to December 10th, 2021.

4 Empirical Analysis - Measuring the Greening of ECB's Communication on Credit Default Swaps

As said in the introduction, we build a new exhaustive CDS spreads database for our sample period. In this section, we first begin by describing the CDS spreads data, and also the control variables that could potentially impact credit spreads (Collin-Dufresne et al., 2001; Han & Zhou, 2015; Galil et al., 2014; Koutmos, 2019). We present summary statistics, before turning to the description of our methodological framework.

4.1 Data

4.1.1 Dependant Variable - Credit Default Swap (CDS) spreads

Credit derivatives are claims that permits to isolate credit risk from other kinds of risks to allow its trade. It transfers credit risk on the relevant reference entity from protection buyer to protection seller. CDS are traded over the counter (OTC). CDS spreads (expressed in basis points regarding the insured notional amount) represent the annuity premium that the buyer pays to the seller to get this protection.

CDS spreads are extracted from Refinitiv. Due to the absence or the lack of data before 2007, our sample first contains CDS spreads from January 2007 to December 2021. In order not to have biased results due to the impacts of the Subprime Crisis as well as the Sovereign Debt Crisis, we decided to drop data on the 2007-2012 time period. Our final sample displays CDS spreads from January 2013 to December 2021.

We collect CDS spreads across tenor of 5, 10 and 30 years for 168, 187 and 137 firms based in North America respectively (Canada and the USA). All our CDS are traded in US dollars. We keep only data on dates a speech (or multiple) was given by ECB boards members. If a speech was given on a week-end day, we interpolate CDS spreads. We excluded all CDS with more than 70% of missing values. Due to the high frequency of speeches that contain relatively high proportion of the topic "Climate Change", we also exclude CDS that have more than 70% of missing values during the year 2021.

Results of the Augmented Dickey-Fuller Test on our CDS time series show that they are non-stationary. In panel quantile regression, non-stationary time series could yield spurious results (Koutmos, 2019). Following Blasberg et al. (2021), we analyze first-level differences. We calculate the daily CDS spread log returns in the same way:

$$s_{i,t}^m = \log(CDS_{i,t}^m) - \log(CDS_{i,t-1}^m) \tag{1}$$

where $CDS_{i,t}^m$ is the m-year CDS spread of firm i at day t. $s_{i,t}^m$ quantifies the daily relative change in a firm's CDS spread.

4.1.2 Control Variables

In line with the financial literature on the determinants of CDS spreads, we control for market-specific and firm-specific variables that have been shown to have an impact on CDS spreads (Ericsson et al., 2009; Han & Zhou, 2015; Galil et al., 2014). Firm-specific variables include stock returns and the VIX for individual firm's expected volatility in line with Collin-Dufresne et al. (2001). For market specific variables we include the risk-free interest rate (IR) and general market conditions.

Firm-specific variables The literature studying spreads highlights the crucial role of stock returns as the principal determinant of CDS spreads, and the main explanatory variable of a firm's probability of default. Similarly to Blasberg et al. (2021), we include it in our model as the difference of the natural log of daily stock prices of the firms present in our sample: $r_{i,t} = \log(S_{i,t}) - \log(S_{i,t-1})$ where $S_{i,t}$ represents the stock price of firm i at time t (also obtained from Refinitiv). We include the VIX indicator to control for volatility. As the VIX indicator is the average of annualized volatility of S&P500 firms, it is commonly used in the literature to proxy for asset volatility (Collin-Dufresne et al., 2001). As the literature shows, the probability of default of a firm increase with the volatility of the market. Therefore, we expect a positive relationship between CDS spread and changes in the VIX.

Market-specific variables We follow Collin-Dufresne et al. (2001) and Han and Zhou (2015) and include the risk-free interest rate (IR) proxied by the change in the German 10-year Government Bond (ΔIR_t) extracted from the Bundesbank database. Finally, we use the Median Rate Index (MRI) to measure market general conditions. We follow the methodology of Galil et al. (2014) and Blasberg et al. (2021) to calculate the change in business climate in calculating the MRI index. The Median Rate Index is defined as the median spread change of all firms in the same rating group. We classify firms using four groups: "AAA/AAs", "As", "BBBs" and "BB+ and lower". As in Galil et al. (2014), we expect to see a positive relationship between MRI and CDS spreads.

4.2 Summary Statistics

Table 1 presents descriptive statistics for all dependent and independent variables used in our study. Average CDS spread returns is the same across our three different maturities (5-, 10- and 30-year contracts) and is situated slightly below zero. Relatively small dispersion can be deduced from the corresponding standard deviation, CDS spread returns varying between 4.1% and 5.2%. Our sample of CDS spread returns comprises sizable outliers with maximum returns from 170% to 192% and minimum returns varying from -119% to -175% across our three different maturities. CDS spread return distributions for our three maturities is right-skewed and very heavy-tailed (relative to a normal distribution), with a kurtosis ranging from 107 to 143.

Variable	Mean	Q25	Median	Q75	SD	Min	Max	Skew	Kurt
				Dependant Variables					
$s^5_{i,t}$	-0.0004	-0.0104	0.0000	0.0051	0.0529	-1.1933	1.9208	2.9469	107.5042
$s^{10}_{i,t}$	-0.0004	-0.0080	0.0000	0.0047	0.0438	-1.7478	1.7029	2.0167	143.2466
$s^{30}_{i,t}$	-0.0004	-0.0074	0.0000	0.0046	0.0417	-1.6297	1.7189	1.9478	135.4099
				Independent Variables					
$\Delta CCtopic_t$	0.0038	-1.5839	-0.0302	1.5531	2.573	-8.8869	8.8982	0.0556	0.7739
$r^5_{i,t}$	0.0009	-0.0102	0.0012	0.0126	0.0374	-1.7167	1.1685	-2.9131	129.1615
$r^{10}_{i,t}$	0.0009	-0.0101	0.0012	0.0125	0.0369	-1.7167	1.1685	-2.8344	126.7275
$r^{30}_{i,t}$	0.0009	-0.0099	0.0012	0.0124	0.0345	-0.9078	0.7411	-2.0183	64.3461
ΔVIX_t	0.0004	-0.0569	-0.0039	0.0480	0.1153	-0.5523	0.9911	1.5168	11.7935
$\Delta MRI^5_{i,t}$	-0.0007	-0.0138	0.0000	0.0094	0.0485	-0.2969	1.1036	6.4482	149.5036
$\Delta MRI^{10}_{i,t}$	-0.0006	-0.0106	0.0000	0.0070	0.0345	-0.2759	0.8307	6.1763	156.6420
$\Delta MRI^{30}_{i,t}$	-0.0006	-0.0096	-0.0002	0.0060	0.0291	-0.1794	0.5828	3.7544	74.7234

Table 1: This table presents descriptive statistics (mean, 1st quartile, median, 3rd quartile, standard deviation, minimum, maximum, skewness and kurtosis) for all dependent and independent variables in our sample

4.3 Methodology - Panel Quantile Regression

Linear models commonly used in the financial literature focus on the estimation of the conditional mean of the dependent variable given one or several explanatory variables. Because our CDS distributions is heavily right-tailed, we opted for the use of quantile regression, therefore allowing for a more precise description of the tails of the distribution. Due to its robustness to leptokurtosis, heteroskedasticity and skewness (three common features of financial data), this approach is increasingly used in both theoretical and empirical financial literature since its introduction by Koenker and Bassett (1978) (Barnes & Hughes, 2002; Baur et al., 2012; Galvao & Kato, 2016).

We follow Blasberg et al. (2021) and adopt the quantile regression framework for a panel setup with firm fixed-effects. Following previous literature on CDS determinants (Collin-Dufresne et al., 2001; Ericsson et al., 2009), we include key known determinants of CDS spread returns in our baseline quantile regression:

$$Q_{s^m_{i,t}}(\tau|x_{i,t}) = \beta_{\tau,1}\Delta CCtopic_t + \beta_{\tau,2}r^m_{i,t} + \beta_{\tau,3}\Delta VIX_t + \beta_{\tau,4}\Delta MRI^m_{i,t} + \alpha_{\tau,i} + \varepsilon_{i,t},$$

where $s^m_{i,t}$ is the daily relative change of the m-year CDS spread of firm i at day t, $\tau \epsilon \{0.1, ..., 0.9\ \}$ is the fixed decile level, $x_{i,t}$ is the m-dimensional covariate vector where $i = 1, ..., N$ and $t = 1, ..., T$, $\Delta CCtopic_t$ is the frequency of the topic labeled "Climate Change" in ECB's speech on day t, $r^m_{i,t}$ is the stock return of firm i on day t for the m-year CDS maturity, VIX_t is the VIX index on day t, $MRI^m_{i,t}$ is the Median Rated Index for firms of the m-year CDS spread returns, $\alpha_{\tau,i}$ is the firm-specific fixed effects parameters, and, finally, $\varepsilon_{i,t}$ is the error term.

The model is run for every decile $\tau \in$ {0.1,..., 0.9} in order to isolate the effect of each explanatory variable on the entire conditional distribution of CDS spread returns. The mid decile ($\tau = 0.5$) corresponds to the unchanged CDS spread case. If CDS spread increases ($\tau > 0.5$), firm's creditworthiness deteriorates. On the other hand, if CDS spread decreases ($\tau < 0.5$), firm's creditworthiness improves.

5 Empirical Results

5.1 Main Results

Table 2 reports our estimated coefficients at different deciles for each maturity (5, 10 and 30 years). First, for our statistically significant coefficients, we observe a positive relationship between CDS spread returns and our variable on ECB's communication about climate change. Thus, an increase of ECB's communication on the topic of climate change leads to a rise of CDS spread returns of all firms contained in our sample. It is economically significant: the higher the frequency of ECB's communication about climate change is, the higher market's perception of a regulatory risk will be. This will lead to an increase of a firm's probability of default, making its CDS spread returns rise. For example, considering the 5Y tenor, a one standard deviation increase in ECB's communication about climate change (2.573) is associated with a rise of 0.015 (= 2.573 x 0.006) percentage points in the CDS spread returns of the firms of the 9th decile, the riskiest ones. This account of 0.28% of the standard deviation of CDS spread returns.

Moreover, we observe that the level of significance of our estimated coefficients decreases over maturities. When we find three coefficients statistically significant at the 0.1% level (for the 7th, the 8th and the 9th decile) for the 5Y tenor, we find only coefficients statistically significant at the 5% level for the 10Y tenor, and almost none statistical significance for the 30Y tenor. That is, the increase in climate transition risk has a greater impact on short and medium-term CDS spreads than on long-term ones. Thus, market participants anticipate an increase in firms' probability of defaults in the short and medium term rather than in the long term.

Finally, coefficients are increasingly larger and significant in the first three deciles (1st, 2nd and 3rd deciles) and in the last three deciles (7th, 8th and 9th deciles) of the distribution. That is, an increase of the climate transition risk (proxied by ECB's communication about climate change) leads to a state where the safest firms become risky, and the riskiest firms become even riskier. These results are consistent with our hypothesis: there is a positive relationship between climate transition risk and CDS spread returns. The extremes of the conditional distribution of CDS spread returns are where this relationship is the strongest.

	1	2	3	4	5	6	7	8	9
					5Y				
ΔCCtopic	36.55*	31.94**	13.68*	2.46	-0.73	1.58	18.09***	36.10***	60.55***
	(16.65)	(8.53)	(5.82)	(3.03)	(2.28)	(2.62)	(4.53)	(7.04)	(12.73)
StockReturn	-796.21***	-658.88***	-477.01***	-287.27***	-189.23***	-221.05***	-367.86***	-570.97***	-857.30***
	(113.38)	(92.94)	(68.49)	(53.04)	(40.56)	(47.65)	(63.22)	(102.65)	(158.61)
ΔVIX	613.61***	479.35***	364.40***	239.60***	156.17***	200.99***	379.60***	601.73***	929.52***
	(37.82)	(38.22)	(40.06)	(40.27)	(32.89)	(34.42)	(44.04)	(49.10)	(48.11)
ΔMRI	2222.84***	23.05***	22.62***	22.69***	22.78***	22.89***	23.89***	26.23***	28.74***
	(1.38)	(1.54)	(1.61)	(1.75)	(1.84)	(1.84)	(1.78)	(1.81)	(1.69)
					10Y				
ΔCCtopic	26.41*	10.92*	7.48*	-1.01	-1.03	-2.52*	6.16	12.83*	19.23
	(12.47)	(4.24)	(3.82)	(2.58)	(1.20)	(1.78)	(3.56)	(5.47)	(10.24)
StockReturn	-643.84***	-506.48***	-376.98***	-202.98***	-134.11**	-164.22**	-292.87***	-544.42***	-929.76***
	(122.67)	(82.39)	(74.86)	(56.19)	(44.06)	(51.27)	(62.51)	(94.29)	(117.82)
ΔVIX	639.44***	485.94***	366.62***	227.89***	132.53***	162.76***	334.95***	528.59***	818.24***
	(30.96)	(28.92)	(31.48)	(37.69)	(30.69)	(33.83)	(34.08)	(32.20)	(35.40)
ΔMRI	2.71***	2.94***	2.65***	2.17***	1.83***	2.19***	3.25***	4.61***	5.98***
	(0.65)	(0.68)	(0.64)	(0.58)	(0.54)	(0.61)	(0.74)	(0.80)	(1.13)
					30Y				
ΔCCtopic	13.95	11.51	6.08	-0.19	-0.26	4.92	11.19**	12.23*	38.41*
	(14.71)	(7.81)	(5.29)	(2.97)	(1.67)	(3.01)	(4.28)	(6.19)	(11.72)
StockReturn	-438.19**	-358.13***	-282.42***	-174.68***	-123.75**	-139.16**	-224.81***	-376.59***	-606.76***
	(136.57)	(83.68)	(66.49)	(50.09)	(39.77)	(45.81)	(67.31)	(100.20)	(130.02)
ΔVIX	371.39***	305.64***	232.23***	156.98***	106.30***	136.27***	249.33***	355.94***	527.65***
	(36.51)	(29.65)	(28.03)	(27.06)	(21.50)	(21.70)	(28.79)	(30.94)	(34.60)
ΔMRI	15.82***	14.77***	14.01***	13.39***	13.33***	13.60***	14.80***	16.89***	19.22***
	(1.47)	(1.51)	(1.73)	(1.77)	(1.84)	(1.82)	(1.80)	(1.58)	(1.65)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 2: This table reports the coefficient estimates of the base panel quantile regression model for 5-year (top), 10-year (center), 30-year (bottom) CDS spread returns. All variables are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all the nine deciles. All estimates are scaled by factor 1e04.

5.2 Sectoral Results

Literature on transition risks provides evidence on the difference of exposition according to sectors firms are embedded in. More specifically, some papers demonstrate that carbon-intensive industry such as energy or basic materials will be more impacted by transition risk and stranded assets than low-carbon ones (Dietz et al., 2016; Dietz et al., 2020).

We try to provide empirical proof to validate these findings, we follow Blasberg et al. (2021) and re-estimate our baseline quantile regression, regrouping the firms by using Refinitiv's 9-sector classification (TRBC 2020). We include sector dummies and interaction terms with our CCtopic variable in the baseline regression. Our new equation is as follows:

$$\begin{aligned} Q_{s^m_{i,t}}(\tau|x_{i,t}) = {} & \beta_{\tau,1}\Delta CCtopic_t + \beta_{\tau,2} r^m_{i,t} + \beta_{\tau,3}\Delta VIX_t + \beta_{\tau,4}\Delta MRI^m_{i,t} + \alpha_{\tau,i} \\ & + \sum_{j=5}^{12} \beta_{\tau,j} Sector_i + \sum_{k=13}^{20} \beta_{\tau,k} Sector_i \Delta CCtopic_t + \varepsilon_{i,t}, \end{aligned}$$

where $Sector_i$ indicates firm i's Thomson Reuters Business Classification (TRBC) classification.

Table 3 reports the coefficient estimates of the interaction terms of our sector panel quantile regression for 5-year CDS spread returns. Almost all our coefficients are significant and negative. This provides evidence that investors anticipate that firms from all sectors present in our sample have already integrated the risk of future regulation coming from central banks on the subject of climate change. They are seen as capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation in the short-term. Furthermore, the coefficients on the interaction term between the sector and our communication variable are practically all non-significant for Consumer Cyclicals (CCGS), Healthcare, Technology and Utilities. As a result, these sectors show the most uncertainty in the implementation of the transition.

	1	2	3	4	5	6	7	8	9
BM x ΔCCtopic	-183.11**	-135.54***	-64.54**	-37.18*	-55.91***	-39.16	-14.46	-134.34**	16.68
	(73.33)	(37.57)	(24.80)	(17.71)	(14.32)	(21.80)	(42.17)	(41.63)	(114.90)
CCGS x ΔCCtopic	-84.05	-66.13	-16.45	-22.20	-36.19**	-16.12	-13.00	-92.42***	47.27
	(63.59)	(34.22)	(12.24)	(16.40)	(12.03)	(17.42)	(27.70)	(24.40)	(99.47)
NCGS x ΔCCtopic	-97.60	-121.62***	-27.10	-35.95	-49.69**	-19.62	-4.61	-118.76***	73.07
	(70.88)	(34.95)	(18.56)	(18.93)	(17.38)	(22.37)	(33.43)	(28.87)	(112.49)
Energy x ΔCCtopic	-221.30**	-161.14***	-73.24**	-57.41***	-68.98***	-60.58*	-48.24	-191.14***	-174.35
	(81.30)	(42.93)	(22.76)	(17.19)	(14.23)	(24.88)	(36.23)	(37.76)	(119.10)
Finance x ΔCCtopic	-133.82	-72.04	-48.73*	-43.95**	-52.54***	-34.85	-45.12	-111.86***	10.83
	(94.99)	(41.11)	(19.69)	(16.53)	(10.79)	(18.73)	(29.02)	(32.02)	(99.15)
Healthcare x ΔCCtopic	-90.66	-42.83	-14.54	-17.88	-34.73**	-21.97	-4.93	-78.65**	68.46
	(70.57)	(34.06)	(13.27)	(18.40)	(12.86)	(19.18)	(27.03)	(27.94)	(107.16)
Industrials x ΔCCtopic	-204.05**	-110.52**	-42.54*	-38.98**	-50.17***	-33.66	-18.21	-82.49*	46.40
	(68.24)	(35.70)	(17.53)	(15.08)	(10.52)	(17.74)	(27.95)	(35.64)	(107.15)
Real Estate x ΔCCtopic	-323.87**	-162.74***	-55.24	-34.06	-49.04***	-34.11	-21.26	-67.84	125.78
	(114.88)	(36.04)	(35.53)	(20.77)	(11.74)	(18.23)	(31.38)	(49.62)	(109.42)
Technology x ΔCCtopic	-58.19	-47.43	19.68	-25.75	-41.35***	-25.05	-9.13	-101.03**	7.98
	(70.91)	(36.36)	(11.43)	(16.31)	(10.79)	(17.96)	(27.40)	(33.68)	(106.71)
Utilities x ΔCCtopic	-257.20*	-103.20	-38.51	-57.09**	-58.10***	-30.89	-11.59	-56.10	-9.42
	(102.85)	(53.77)	(23.77)	(19.55)	(10.85)	(19.44)	(27.46)	(32.72)	(114.01)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 5-year CDS spread returns. All variables are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e04. Estimations and confidence intervals are computed over B = 5,000 bootstrap replications.

We run the same sector panel quantile regression model for 10-year CDS spread returns. No significant coefficients were found. Therefore, the increasing communication of the ECB on the topic of climate change has no impact on investors' expectation of firms' probability of default in the medium term. Finally, Table 4 presents the coefficient estimates of the interaction terms of the sector panel quantile regression model for 30-year CDS spread returns. At this maturity, almost our coefficients are strongly significant (at the 1% level) and positive. Therefore, a growing communication of central banks on the subject of climate change could translate into higher probability of default in the long term for firms in our sample, regardless of sectors.

These results differ from Blasberg et al. (2021). In our case, we provide empirical evidence on potential nonlinear effects of the communication of the ECB on the topic of climate change on CDS spread returns. As such, in the short term, market actors seem to have integrated the fact that a potential regulation coming from the ECB to mitigate the effects of climate change on financial markets, and firms are already seen as capable of transitioning to a low-carbon economy. But in the medium term (10-year maturity), it seems that financial actors are uncertain over the implementation of climate change mitigation regulations from the ECB. Finally, in the long-term (30-year maturity), our coefficients estimates of the interaction terms of the sector panel quantile regression become positive and highly significant. CDS markets' participants expect a higher probability of default for firms across all sectors in the very long-term with the increase of ECB's communication about climate change.

	1	2	3	4	5	6	7	8	9
BM x ΔCCtopic	178.54***	58.56**	57.60**	63.72***	61.30***	49.92***	62.22**	54.61*	130.57**
	(46.13)	(21.46)	(17.68)	(10.84)	(8.75)	(12.26)	(23.87)	(26.74)	(49.01)
CCGS x ΔCCtopic	293.58***	114.97***	112.41***	83.81***	77.07***	67.19***	70.33***	73.49***	133.93***
	(36.27)	(19.68)	(15.88)	(11.01)	(7.16)	(9.21)	(14.34)	(17.87)	(36.58)
NCGS x ΔCCtopic	271.60***	122.26***	118.01***	95.20***	82.08***	63.95***	96.86***	118.18***	228.53***
	(35.87)	(26.34)	(12.45)	(14.19)	(13.55)	(14.33)	(23.98)	(22.54)	(37.83)
Energy x ΔCCtopic	-14.18	94.27*	138.35***	80.36***	64.57***	46.48***	59.62***	52.89**	226.08***
	(80.90)	(39.56)	(35.43)	(9.84)	(4.10)	(4.69)	(5.05)	(18.31)	(39.78)
Finance x ΔCCtopic	108.10***	53.91**	77.30***	72.33***	60.79***	47.41***	58.28***	53.96	119.23***
	(28.45)	(18.07)	(15.69)	(10.31)	(8.98)	(10.11)	(12.72)	(31.57)	(35.66)
Healthcare x ΔCCtopic	88.18*	26.63*	64.17***	53.65***	56.27***	35.21***	35.82***	28.26	95.66***
	(40.33)	(13.16)	(13.48)	(6.88)	(4.08)	(6.34)	(9.68)	(18.19)	(24.57)
Industrials x ΔCCtopic	201.58***	110.61***	118.38***	86.08***	77.39***	65.39***	70.53***	76.34*	118.90**
	(57.54)	(11.78)	(11.74)	(9.68)	(8.16)	(8.14)	(10.61)	(30.68)	(43.72)
Real Estate x ΔCCtopic	170.96***	45.76*	92.80***	67.38***	62.66***	49.20***	64.62***	67.38***	120.06**
	(50.54)	(18.37)	(12.90)	(7.25)	(4.46)	(7.56)	(7.70)	(18.59)	(45.73)
Technology x ΔCCtopic	174.82***	109.24***	107.49***	81.39***	68.50***	62.83***	63.99***	66.46**	88.40***
	(30.48)	(9.86)	(17.12)	(8.80)	(6.81)	(5.29)	(8.43)	(23.25)	(25.55)
Utilities x ΔCCtopic	74.69	60.21***	70.68***	61.72***	58.11***	47.52***	54.72***	50.62*	148.98*
	(58.77)	(15.92)	(13.21)	(8.55)	(4.93)	(6.67)	(12.51)	(21.52)	(62.43)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 30-year CDS spread returns. All variables are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e04. Estimations and confidence intervals are computed over B = 5,000 bootstrap replications.

6 Conclusions

In recent years, an increasing number of scientific publications (e.g. 6 IPCC Reports published from 1990 to 2023) provide unquestionable evidence that climate change will impact our economic system as a whole. These negative shocks affecting the supply and demand functions of the real economy are vectors of instability in the financial system. Transitioning from a high- to a low-carbon economic system as prescribed by net-zero carbon emissions policies requires a drastic change of our productive system. All actors need to take part in this transformation, and this includes central banks. Even if it is not explicitly part of their mandates, central banks should be aware of climate risk.

In this paper, we investigate how the European Central Bank communicates about climate change. We use a topic modelling approach and extracted a topic labeled "Climate Change" from ECB's speeches. We show evidence for an increase in ECB's communication on the topic of climate change. We then investigate the way it communicates, and find out that ECB talks about climate change in terms of a risk for financial stability. Thus, we conclude that the ECB uses its communication as a signal for financial markets that they may implement a regulation to mitigate climate change impacts on the financial system.

We then use panel quantile regression to isolate the impacts of an increase of ECB's communication on the topic of climate change on the expected probability of default for 168 firms (proxied by their CDS spread returns). We investigate 5-, 10- and 30-year contracts. Our findings show an overall positive relationship between lenders' perceived exposure to a regulatory risk from the ECB and the firms' cost of default protection.

In addition, we include sector dummies and interaction terms with our communication variable in our baseline quantile regression and show proof of the existence of nonlinear effects across the short, medium and long term. Our findings show significant and negative coefficients on the short term (5-year maturity), that prove that market actors seem to have integrated a potential implementation of regulation coming from the ECB to mitigate the effects of climate change on financial markets. These results also prove that firms are already seen as capable of transitioning to a low-carbon economy in the short term. In the medium term (10-year maturity), our estimated coefficients are all non-significant, it seems that financial actors are uncertain of how the ECB will act regarding climate risk. Finally, in the long-term (30-year maturity), our estimated coefficients are positive and strongly significant. CDS markets' participants expect a higher probability of default for firms across all sectors in the very long-term with the increase of ECB's communication about climate change.

Overall, we highlight how ECB's communication can impact investors' expectation of the probability of default of different firms at different time horizons. Our findings are particularly relevant on the regulation of climate risk. Our findings also have important policy implications. They suggest that firms are ready to transition on the short-term, and that central banks should take a more active role to help this transition to a low-carbon system, even by using regulatory tools. Not taking actions now will rise uncertainty about climate change impacts on financial markets, leading to a raise of firms' probability of default that could be the detonator of a new financial crisis.

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