DNB Working Paper
No 798 / January 2024

The European Carbon Bond Premium

Dirk Broeders, Marleen de Jonge and David Rijsbergen

DeNederlandscheBank
EUROSYSTEEM

The European Carbon Bond Premium

Dirk Broeders, Marleen de Jonge and David Rijsbergen*

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 798

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

January 2024

The European Carbon Bond Premium*

Dirk Broeders

De Nederlandsche Bank and Maastricht University

Marleen de Jonge

De Nederlandsche Bank

David Rijsbergen

De Nederlandsche Bank

January 12, 2024

Abstract

We document a positive and statistically significant carbon premium that investors demand for investing in bonds issued by high carbon-emitting firms in the euro area. Over the entire sample period, we estimate that doubling a firm's Scope 1 and 2 emissions results in an average increase of 6.6 basis points in the spread on the firm's issued bonds. In addition, we find that the carbon premium has increased since 2020 and the effect reached 13.9 basis points by early 2022. These results suggest that European companies with high levels of carbon emissions are experiencing progressively higher financing costs. Our research also reveals a distinctive carbon premium term structure, rising with longer maturities. Interestingly, over time the term structure flattens, suggesting investors' confident anticipation of ongoing carbon pricing in the European Union at a stable pace.

JEL classification: G12, G15, G23, Q51, Q54

Keywords: Carbon Premium, Carbon Premium Term Structure, Climate Change, Climate Transition Risk

*Dirk Broeders (corresponding author): d.w.g.a.broeders@dnb.nl; Marleen de Jonge: m.r.h.de.jonge@dnb.nl; David Rijbergen: d.r.rijsbergen@dnb.nl. We thank Jan Bauer and Sanchayan Banerjee of VU University for helpful guidance and feedback in the early stages of this work. We also thank Maurice Bun and Aerdt Houben, and participants at the DNB seminar for valuable feedback on earlier versions of the paper. The views expressed in this paper are those of the authors and do not reflect the views of De Nederlandsche Bank, or the Eurosystem.

1 Introduction

The transition to a low-carbon economy entails large-scale structural shifts in the global economy; shifts that most likely come with shocks and financial disruptions (Bolton et al., 2020). High carbon-emitting firms are exposed to these transition risks. Profound policy, legal and technological developments as well as changes in consumer preferences, will particularly target corporate carbon and other greenhouse gas emissions. Many firms face increasingly high emission expenses as emission taxation and pricing strengthen. Moreover, climate litigation gains momentum, exemplified by impactful cases such as *Milieudefensie et al. v. Shell*.[1] This trend is anticipated to grow further, with financial institutions becoming increasingly subject to climate-related legal actions (Setzer and Higham, 2022). As networks of firms, financial institutions, and households are intricately connected, transition risk may reverberate and pose a threat to overall financial stability (Battiston et al., 2017; Campiglio and der Ploeg, 2021). Price discovery of transition risks in financial markets is therefore essential; it supports adequate risk management and an efficient allocation of resources in the economy.

Investors in financial assets issued by high-emission firms demand compensation for transition risk in the form of a "carbon premium", where they regard a firm's carbon emissions as a reliable risk indicator (Giglio et al., 2021). Moreover, investors seek compensation for uncertainties surrounding impending climate policies, legislation and regulations. Investors may also opt to avoid high-emitting firms due to ethical, moral, or reputation considerations. Consequently, this exerts downward pressure on the prices of securities from high-emitting firms.

A number of papers confirm the presence of a positive carbon premium across different asset classes and regions, predominantly in US bond and equity markets

[1] The verdict in the *Milieudefensie v. Shell* case, in which the District Court of The Hague ruled that Shell is obligated to reduce emissions from its operations by 45% by 2030 compared to 2019 levels, is poised to have significant implications throughout the corporate landscape (Setzer and Higham, 2022).

(Bolton and Kacperczyk, 2020, 2021b; Alessi et al., 2019; Xia and Zulaica, 2022; Brown and Watkins, 2015; Dell'Anna and Bottero, 2021). Boermans et al. (2024) document a carbon premium which is significantly lower for companies engaging in green innovation. Interestingly, other studies present contrasting findings of a negative carbon premium, suggesting that investors prefer to invest in carbon-intensive firms and assets (In et al., 2017; Bernardini et al., 2021; Huij et al., 2022; Pástor et al., 2021), while there are also papers that find no statistically significant premium associated with carbon emissions (Aswani et al., 2023; Witkowski et al., 2021). Loyson et al. (2023) deploy several econometric methods to test the presence of a carbon premium and find mixed results; while they find evidence for a rising carbon premium after the Paris Agreement using treatment effect models, they find no support using a panel regression, a long-short portfolio and error correction model. Bauer et al. (2022) attribute inconsistencies in the current literature to varying choices in sample periods and compositions, and in measures of environmental performance and statistical approaches.[2] In order to go beyond the discussion centred on sampling choices, enhancing our understanding necessitates evaluations at more detailed levels that fluctuate with time and sample composition.

Research on the carbon premium in European markets is limited. A few papers focus on the pricing of transition risks in European stock markets (Bernardini et al., 2021; Alessi et al., 2019). So far Bats et al. (2023) is unique in exploring transition risk pricing in the European bond market using textual analysis. Research on the carbon premium in the European bond market is essential for two key reasons. First, the carbon premium in the European market may be further developed than in other regions, reflecting the heightened progressiveness of the European Union's dedication to attaining net-zero status and the stringent implementation of com-

[2] A firm's environmental performance can be inferred from emission level data, emission intensity figures, or composite environmental scores. Other discrepancies emerge from variations in statistical approaches, particularly in clustering standard errors and including specific control variables. The composition of firms in the sample and the chosen sample period further contribute to the inconsistencies (Bauer et al., 2022).

prehensive climate policies. Second, debt financing carries substantial significance in the European bank-based economy (Bats et al., 2023), implying again that the European carbon premium could appear differently than in the US or other regions.

In this paper, we quantify the carbon premium that investors demand when investing in bonds issued by high carbon-emitting firms in the euro area. Specifically, we derive time-average and time-varying coefficients for the carbon premium in a sample of 1,751 corporate bonds issued by 368 non-financial firms situated in the euro area. Our analysis covers the period from January 2016 to December 2022. We use firm-level emission data from MSCI ESG Manager and bond- and firm-level variables from Bloomberg and Refinitiv to construct a panel regression explaining bond yield spreads relative to the risk-free rate. We calculate the carbon premium by quantifying the effect of a firm's carbon emissions on bond yield spreads, after controlling for bond- and firm-specific variables. Furthermore, we extend the model to a time-varying panel regression to obtain monthly coefficients for the carbon preference premium over the sample period. We also study how the carbon premium term structure develops over time.

Our main finding is a positive carbon emission premium in euro area corporate bonds. The premium has been significant and positive since mid 2020, after being negative or insignificant for years. The result is statistically and economically significant. Over the full sample period, we estimate that a doubling in a firm's Scope 1 and 2 emissions increases the spread on the firm's issued bonds by an average of 6.6 basis points. This is almost twice as high as the carbon premium in the US bond market that Xia and Zulaica (2022) estimate. Moreover, we find that the carbon premium has rapidly increased in recent years starting from early 2020. For example, by 2022, we find that the same doubling of carbon emission increases the average spread on euro area corporate bonds by 13.9 basis points. Hence, European firms with high levels of carbon emissions face increasingly high cost of debt.

We also document a term structure of the carbon premium. Our findings reveal a positive relationship between the size of the carbon premium and bond maturity. Notably, the upward trajectory is particularly pronounced in short-term maturities, gradually levelling off as maturities extend. We also observe that the term structure flattens during the years in our sample period, as the difference in carbon premium between short- and long-term maturity bonds diminishes. This suggests that investors are confidently anticipating ongoing carbon pricing in the European Union at a stable pace.

Finally, we observe that the carbon premium moves in tandem with the price of emission allowances issued under the EU Emissions Trading System (EU ETS). More research is needed to assess a potential causality between the two prices. Potential co-integration of the two prices can provide insights into how the carbon premium might develop in various scenarios of emission pricing and consequently, how the carbon premium affects corporate financing costs.

We add to the existing literature in two key ways. First, we bridge a geographical-asset class gap in existing literature by examining the carbon premium in the euro area bond market. Bats et al. (2023) is the only reference investigating transition risk pricing in the European bond market, but in this study, transition risk is derived from the bond's sensitivity to climate news, rather than from firm-level emissions. Second, we take a time-varying approach to make our results less sensitive to sampling decisions and to obtain insights in the time dynamics of the carbon premium. Our results suggest that prior studies attempt to identify a carbon premium in a sample period starting well before its discernible emergence, resulting in often statistically insignificant findings.

The remainder of this paper is structured as follows. Section 2 explores the theoretical and conceptual foundation of transition risk pricing and the carbon premium. Section 3 describes the data sets we use, as well as statistical properties of the sample of bonds that we analyse. Section 4 explains the set-up and documents the results of the empirical analysis for the carbon premium and the carbon premium term structure over the whole sample period. In Section 5 we describe how the carbon premium develops over time. Finally, Section 6 concludes with a discussion for further research.

2 Theoretical Background

European firms subject to the regulatory framework of the EU ETS face increasingly high prices for carbon emission allowances, which will likely continue to rise in the coming years (Gerlagh et al., 2022). The escalating prices for carbon emission allowances pose financial challenges for firms, impacting their operational costs and necessitating strategic adjustments to mitigate economic implications. Moreover, firms may be negatively affected by heightened volatility in carbon prices. Especially in times of economic downturn or decreased confidence in the EU ETS, prices may be volatile (Lutz et al., 2013). Moreover, changing consumer preferences, negative screening by investors, legislative restrictions, a deteriorated reputation or higher imposed taxes may increase business costs. High-emission firms are at a greater risk of encountering frequent negative cash-flows and more volatile asset values compared to their lower-emission counterparts (Kabir et al., 2021).

Recently, climate litigation has emerged as a prominent new form of transition risk; the increasingly recognized and utilized role of courts in climate governance underscores its significance. The definition of climate litigation itself has generated extensive debate (Peel and Osofsky, 2020); climate-related court cases may support or prevent climate action and this outcome may be intentional or unintentional. However, it is evident that the number of strategic climate-related cases is significantly on the rise, now encompassing a broad spectrum of actors such as governments, firms, and financial institutions (Setzer and Higham, 2022). Some important wins have occurred, which have already had major repercussions across the corporate community. In 2015, the case *Urgenda Foundation v. State of the*

Netherlands was the first case in which the inaction of a national government was successfully challenged. Many litigation cases followed this landmark case (Setzer and Higham, 2022). Firms have been subject to climate litigation since the case of *Milieudefensie v. Shell*, in which the District Court of the Hague ruled that the major oil company Shell was obliged to cut emissions from its operations by 45% by 2030 compared to 2019 levels. Future trends in climate litigation are expected to progressively target financial institutions who finance high carbon-emitting firms (Koeman et al., 2023; Setzer and Higham, 2022).The risk of litigation has become a pressing component of transition risk, exerting an increasing impact on the financial system.

The academic literature typically distinguishes between two mechanisms in which financial markets price transition risk in corporate bonds (Xia and Zulaica, 2022). The first mechanism, known as the *risk channel*, involves the quantitative assessment of the potential extra credit risks associated with a firm's transition towards a more sustainable business model. This entails an analysis of the inherent uncertainties and vulnerabilities linked to the transition process, influencing the pricing of corporate bonds. The second mechanism, referred to as the *preference channel*, underscores the role of investors' preferences and sentiments in pricing dynamics. This may lead to an additional, credit-risk adjusted, premium that emerges from investors' preferences due to moral or reputation considerations, or from a general belief that not all transition risks are reflected in existing measures of credit risk.

Through the risk channel, transition risk increases conventional credit risk measures, such as credit-default swap spreads, Merton's distance-to-default measures and Bloomberg's DRSK default probabilities.[3] Blasberg et al. (2021) show that a firm's exposure to transition risk is a relevant determinant for the level of its CDS-spreads, from which again several market-based measures of corporate credit risk

[3]Bloomberg's DRSK default probabilities refer to a risk assessment model developed by Bloomberg, which estimates the likelihood of a firm defaulting on its debt obligations (Bondioli et al., 2021). This model is widely used in financial analysis and investment decision-making.

are derived. Further, Capasso et al. (2020) find that there is a negative correlation between a firm's distance-to-default and its carbon emissions and carbon intensity. This implies that, all else being equal, the market perceives firms with larger carbon footprints as having a higher default probability.

Through the preference channel, investors seek additional compensation for transition risks that are assumed not to be reflected in corporate credit risk measures. According to Pástor et al. (2021), the assets managed with a sustainability focus now amount to tens of trillions of dollars, with the potential for further growth. This preference may lead to an increase in the prices of assets for low-emission firms and a decrease for high-emission firms. Pástor et al. (2021) indicate that investors are willing to pay more for green assets, for the sake of social impact rather than risk exposure reduction. Xia and Zulaica (2022) find that a significant carbon premium exists in the US corporate bond market that is uncorrelated with default probability.

Interestingly, climate-related transition risks are often referred to as tail risks, which are not adequately captured by conventional risk metrics due to their low probability yet potentially high-impact nature.[4] These tail risks can encompass sudden and severe events like regulatory changes or technological breakthroughs that drastically alter the market for carbon-intensive firms. Moreover, the dynamics of contagion through banks and investment funds are often underestimated or omitted (Roncoroni et al., 2021). As such, the carbon premium may reflect not only risks or preferences, but also an assessment of these less predictable, high-impact factors. We now turn to a description of the data that we use in our empirical study.

3 Data

Our sample consists of 1,751 corporate bonds issued by 368 non-financial firms located in the euro area, which are observed monthly between January 2016 and

[4] In this paper we focus on transitions risk. Climate-related physical risks are also tail risks and surrounded with fundamental uncertainty.

December 2022. The panel is unbalanced, meaning that not all bonds are observed in each month: the total sample comprises 82,486 observations. Monthly bond- and firm-level variables are collected from MSCI ESG Manager, Refinitiv Eikon and Bloomberg. The sample period starts just after the adoption of the Paris agreement, as several studies have demonstrated structural breaks or jumps in carbon emission pricing after the Paris agreement (Bolton and Kacperczyk, 2021a; Monasterolo and de Angelis, 2018; Monasterolo and De Angelis, 2020).

We draw static variables from Refinitiv Eikon: these variables include the bond's unique ISIN, maturity, issue date, coupon, whether or not the bond is callable, and the amount issued (in EUR). We then provide the list of ISINs as input to Bloomberg and extract monthly data between January 2016 and December 2022 on bond- and firm-specific variables. For bond prices, we use option-adjusted spreads relative to the risk-free rate. On the bond-level, we further include credit rating, age, coupon, duration, issued amount (log), illiquidity (measured through bid-ask spreads), and whether or not the bond is callable by the issuer. On the firm-level, we include default probability and volatility of the return on equity measured as the six-month trailing standard deviation of the firm's stock returns.

Below we discuss the sample's composition of bonds (Section 3.1), the credit spread (Section 3.2), the emission data (Section 3.3), and the choice of control variables influencing credit spreads (Section 3.4).

3.1 Bond selection

In the sample selection process, we start with the comprehensive universe of all bonds and then refine the sample by applying various criteria within the Refinitiv Eikon database. The initial criterion for reduction centres on the geographical jurisdiction of the firm's incorporation; specifically, only bonds issued by firms incorporated within the euro area are considered for inclusion.[5] We then apply a set of filters -

[5]We restrict the sample area to the euro zone as this ensures uniformity in monetary policy and substantial economic integration.

in line with Bali et al. (2021), Xia and Zulaica (2022) and Bats et al. (2023) - to ensure sufficient homogeneity of the sample. We exclude the following:

a) Bonds issued by banks and other financial institutions;
b) Perpetual bonds;
c) Floating coupon rate securities;
d) Structured notes, and asset-backed or equity- or index-linked securities;
e) Bonds issued through private placement and issued under the 144A rule;
f) Convertible bonds;
g) Bonds with a maturity shorter than one year;
h) Unrated bonds; and
i) Bonds trading under EUR 5 or above EUR 1,000.[6]

We exclude bonds issued by banks and other financial institutions from our analysis because, although prolific bond issuers, these entities generally do not emit substantial amounts of carbon. Additionally, financial institutions typically operate with high leverage. Consequently, their risk profiles may differ significantly from those of non-financial bonds, potentially leading to distinct risk premiums (Foerster and Sapp, 2005). Further, we exclude perpetual bonds as they are not redeemable; floating coupon securities are far less exposed to interest rate risk as the coupon adjusts with interest rate changes; the returns on structured notes are based on the performance of underlying assets, such as options, indices and swaps, which can result in dynamics that vary across different structured notes (Tuckman and Serrat, 2022; Fabozzi, 2007); privately placed bonds are usually less liquid than publicly sold bonds; bonds issued under the 144A rule are privately placed and do not have to comply with disclosure regulations required for registered securities (Livingston and Zhou, 2002); convertible bonds have characteristics of both bonds and stocks;

[6]In accordance with Xia and Zulaica (2022), our selection procedure includes bonds issued in currencies other than the euro. We also consider bonds issued by firms in the euro area but traded on markets outside the euro area. 17.7% of the bonds in our sample are denominated in currencies other than the euro and 2.5% are traded in non-euro area markets. The issue volume of a bond issued in different currencies is converted to euros.

bonds with a maturity lower than a year are typically removed from market indices (Bai et al., 2019); unrated bonds complicate risk assessment; and finally, very low- or high-priced bonds may indicate liquidity concerns.

3.2 Credit spread

For the dependent variable, we download option-adjusted bond spreads (OAS) from Bloomberg. The sample of bonds for this study holds a large proportion of callable bonds and hence option-adjusted spreads should be used to incorporate the bond's risk of early redemption. The calculation of the Bloomberg OAS uses a one-factor, arbitrage-free binomial tree to establish a distribution of interest rate scenarios. OAS then deals with the bond's call schedule to establish the evolution of rates over time. The present value of the callable bond is determined by using the discount rates found in the tree (Boliari and Topyan, 2022). Spreads on non-callable bonds represent the difference in yield between the bond and a risk-free Treasury bond. We winsorise the option-adjusted spreads at 2.5% in the lower and upper quantile to limit the disturbance of outliers.

3.3 Emission data

Our main variable of interest is carbon emission data. We obtain yearly firm-level carbon emission data from MSCI ESG Manager for all firms in our sample for the years 2015 to 2021.[7,8] This MSCI database provides annual emission levels starting from 2008; coverage has gradually increased over the years, as can be seen in Figure 1. Emission levels are published with a one year delay so that we effectively include one-year-lagged carbon emissions in the model. Hence, the sample period of the

[7]Some studies do not employ absolute emissions and advocate for the use of emission intensity as a proxy for transition risk. Emission intensity is emissions per unit output, e.g. sales. We align with Bolton and Kacperczyk (2023), asserting that investors probably do not consider transition risk normalised to sales; emission intensity might depict a firm as decarbonising even if it is rapidly increasing emission levels, as long as total sales are on the rise.

[8]The database does not offer bond-level identifiers; issuer names are paired using string similarity matching and manually matching undetected pairs.

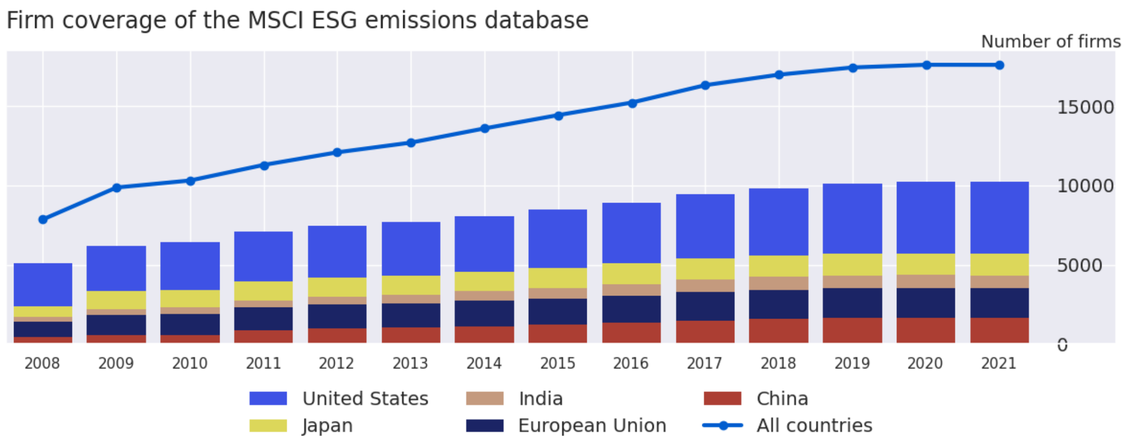

Figure 1: Firm coverage of the MSCI ESG Manager emissions date gradually increases over time. EU firms make up a relatively large part of the sample and have been growing in number.

emission data starts and ends one year before the bond sample.

We retrieve time series data for Scope 1 and Scope 2 emissions for each firm. We leave Scope 3 emissions out of analysis. Scope 1 emissions encompass all emissions originating from sources owned or controlled by the firm, such as direct combustion of fuel in furnaces or vehicles. Scope 2 emissions arise from the generation of electricity procured by the firm. Scope 2 emission levels are typically higher than scope 1 emission levels and demonstrate more variability. Scope 3 emissions encompass all other indirect emissions occurring throughout a company's entire value chain. (MSCI, 2020). These are emissions that are not directly controlled by the firm but are linked to its operations. Scope 3 emissions often constitute the largest portion of a firm's carbon emissions due to their extensive reach. However, quantifying Scope 3 emissions is typically model-based and subject to significant ambiguity and variability, given the absence of a standardized methodology for assessment. Consequently, we choose to exclude scope 3 emissions from our analysis. Figure 2 displays the average level and index of dispersion (variance to mean ratio) for each scope per year.

The emission levels are either reported by the firm or estimated by an MSCI ESG model. In the latter case, MSCI assigns a confidence score to each estimate;

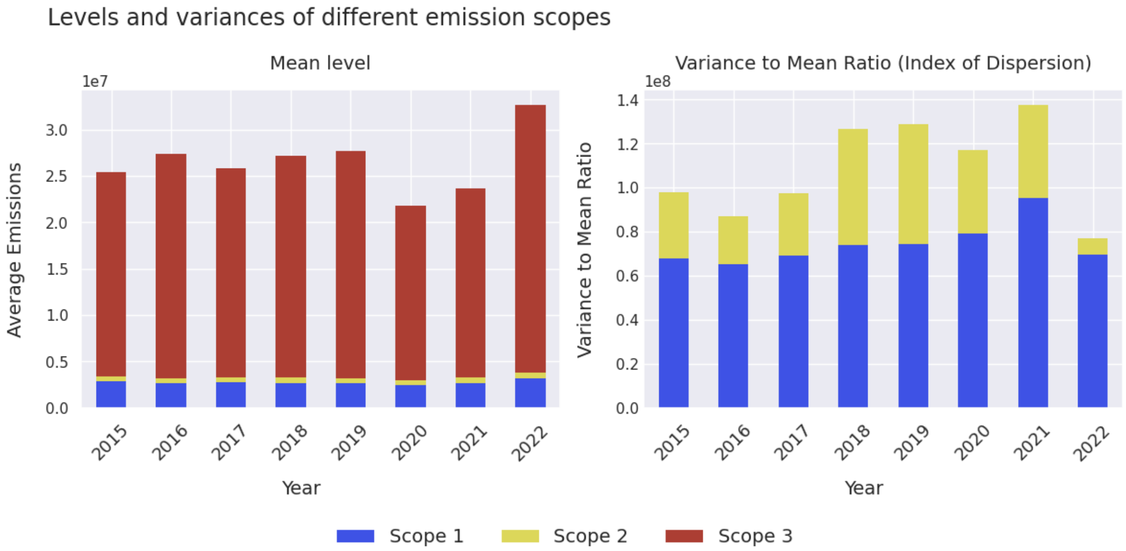

Figure 2: Left: Scope 1, 2 and 3 emissions per year for our sample. Scope 3 is dominant but its measures are often model-based and ambiguously defined. Right: the normalised variances per scope of emissions (variance-to-mean ratio); Scope 3 is omitted given its ambiguous definition and inconsistent documentation. Notably, Scope 1 has much higher variance than Scope 2, also in normalized terms.

we include all observations with a confidence level above "moderately high". For the regression analysis we log-transform the emission data.[9]

3.4 Credit spread determinants

In addition to emission levels, we incorporate bond- and firm-specific variables known to influence bond yield spreads. These factors reflect credit risk, liquidity risk, and refinancing risk. The variables we discuss below attempt to reflect these various sources of risk. All dynamic variables are observed monthly. [10]

To incorporate credit risk, we include the firm's probability of default and the bond's credit rating. We use a probability of default score provided by Bloomberg that reflects the cumulative probability of the firm defaulting within five years.[11]

[9] The log transformation helps to linearize the relationship between emissions and their impact on credit spreads and leads to a more symmetrical distribution of the highly skewed emission data (Xia and Zulaica, 2022), which is critical for the accuracy and validity of the statistical analyses.

[10] Even though several of the described variables reflect similar risks, we show that none of the variables are highly correlated in Appendix A.1.

[11] The score employs a hybrid model incorporating both Merton's distance to default at a specified time horizon t and firm-level variables in a logistic regression (Bondioli et al., 2021).

We draw composite bond credit ratings from Bloomberg, being the averages of the ratings assigned by Moody's, Fitch and S&P.[12] Bond ratings encapsulate crucial aspects such as the bond's payment priority. While the heterogeneity in risk exposure amongst investors of different payment ranks does not necessarily manifest in a firm's probability of default, it is nonetheless reflected in bond ratings. Notably, credit risk and credit ratings are correlated (Hilscher and Wilson, 2017).[13]

We extract the bond's modified Macaulay duration from Bloomberg to quantify the bond's price sensitivity to changes in interest rates.[14] A higher modified duration reflects a higher price volatility risk.

In line with Xia and Zulaica (2022), we include bond age measured in years from issue date to the month of observation. Seasoned bonds typically become less liquid; newly issued bonds typically demonstrate longer maturities and therefore bear more interest rate risk. Studies (Han and Zhou, 2007; Xia and Zulaica, 2022; Lu et al., 2010) have found conflicting results for bond age as a spread determinant. The sign of the effect may change, for example, for low-rated bonds (high-yield bonds) as compared to investment-grade bonds (Han and Zhou, 2007).

We draw the bond's amount issued from Refinitiv, to reflect liquidity considerations and market perception of the bond. As we assume the spread effect to be nonlinear, we log-transform this variable.

We calculate the firm's equity return volatility as the standard deviation over a rolling six month window of monthly log returns, using monthly closing stock prices from Bloomberg.[15] Volatility risk is another significant driver of bond yield spreads (Campbell and Shiller, 1991). This dynamic is partly captured by the

[12] We assign a numerical score to each rating, where 0 equals the rating C and 20 equals the rating AAA.

[13] We incorporate credit ratings in the model as fixed effects so that the correlation and dependency of default risk and credit ratings does not pose a problem of multicollinearity; see Appendix A for further discussion of multicollinearity in the regressors.

[14] If no data are available, we use the closest value available in a time span of three months, before or after the observed month.

[15] If not all six months are available, the number of months is reduced to a minimum window of three months.

default probability, as the default probability encapsulates Merton's distance to default (DD), which has volatility on equity return as a key input (Bondioli et al., 2021). However, the default probability is based on a hybrid model, combining Merton's DD with several other factors, so that risk of volatility in the firm's equity value is only included indirectly.

Additionally, we include a measure of a bond's illiquidity via the bid-ask spread on the last day of the month.[16] Illiquidity compounds the uncertainty and perceived risk associated with a bond, since the prices of illiquid bonds often exhibit greater volatility as it may not be possible to sell the bond at any given moment (Helwege et al., 2014).

Finally, we include the bond's potential call option as a dummy variable. This dummy variable equals one if the bond is callable and zero otherwise. Given the definition and methodology of option-adjusted spreads, callable bonds typically have narrower spreads.

3.5 Descriptive statistics

Table 1 summarises the key statistics of the variables included in the model. The average option-adjusted credit spread across bonds and time is 149 basis points and spans a wide range from -14 to 580 basis points. Negative spreads can be observed as we use option-adjusted spreads which account for the call option of early redemption. The default probability ranges from 3.4% to 49.0%; this range is large due to our use of the *cumulative* default probability over five years. The average credit rating is 12, which equals a BBB rating. In line with the selection procedure, the lowest time to maturity is one year. The average age is 3.7 years and the average coupon 2.7 percent. The average amount outstanding is €627 million, while the largest bond is close to €3 billion. The average monthly equity return volatility is 1.8 percent. The median parameter for illiquidity, measured as the spread between the bond's

[16] If no bid-ask spread is available for the observed month, the closest available spread for that bond within a time span of three months, before or after the observed month, is taken as the value.

Summary statistics sampled bonds					
	Mean	Std. dev.	Min	Median	Max
Option-adjusted spread (bps)[1]	149.3	132.9	-14.4	111	579.8
Default probability[2]	3.4	3.8	0	2.4	49.0
Credit rating	12.3	2.4	2.0	13.0	20.0
Maturity (years)	9.6	10.4	1.0	6.9	98.1
Duration (years)	6.6	3.4	0.0	6.0	23.5
Age (years)	3.7	3.7	0.0	2.7	27.8
Coupon (pp)	2.7	1.9	0.0	2.2	10.0
Amount outstanding (EUR mln)[3]	627.2	332.7	7.4	559.0	2,992.2
Equity return volatility	1.8	1.9	0.0	1.2	34.2
Illiquidity (bps)	77.7	72.4	0.0	64.0	1922.7
Callable (pp)	61.4	-	0.0	1.0	1.0

Table 1: Corporate bond summary statistics; sample period January 2016 to December 2022; sources: Refinitiv, Bloomberg. [1]Option-adjusted spreads are winsorised at the 2.5% fraction. [2]Cumulative five-year-ahead probability of default from Bloomberg. [3]The amount outstanding of bonds issued in currencies other than the euro are converted to euro.

bid and ask price, stands at 77.7 basis points. The maximum illiquidity is 1,922.7 basis points; the high value may arise as we use a single spread at the end of the month, which may temporarily be very high. Finally, note that 61.4% of the sample comprises callable bonds, which reemphasises the need for option-adjusted spreads, rather than regular credit spreads.

To get a better understanding of the data, we also provide summary statistics for the data grouped per sector (Table 2). This makes sense as carbon emissions vary substantially across sectors in the economy (Broeders et al., 2023). We see from the table that the electronics and chemicals sectors typically have low yield spreads; this corresponds to the observed probabilities of default, which are lower in this segment. We also see that the automotive manufacture industry and the transportation industry typically have the highest yield spreads. These two sectors also show the highest average probabilities of default.

Rating-grouped statistics show that, in line with expectations, yield spreads

Summary statistics of sampled bonds by sector					
	Mean OAS	Std.dev. spread	PD[1]	Bond maturity	No. observations:
Chemicals	80	77	1.3%	9.5	4,437
Electronics	81	85	1.1%	7.2	4,510
Gas Utility	92	60	1.9%	6.8	3,956
Beverage/Bottling	96	53	1.3%	10.9	5,639
Oil and Gas	101	87	2.7%	10.5	6,220
Conglomerate/Diversified	103	87	1.6%	7.8	4,911
Service	132	137	3.3%	7.8	12,287
Utility	133	95	3.9%	15.3	12,903
Home Builders	135	83	4.2%	7.2	4,931
Telecommunications	158	122	2.9%	9.7	7,695
Automotive Manufacturer	166	134	4.4%	7.2	4,593
Transportation	177	143	5.1%	7.1	3,943

Table 2: Corporate bond summary statistics by sector; it is clear that bond spreads are higher for higher average default probabilities. The smallest spreads are observed in the electronics and chemicals sectors and the largest in the automotive and transportation sector.[1]Firm default probability is measured as the five-year cumulative probability of default as provided by Bloomberg.

increase almost monotonically with decreasing rating (Table 3). Some exceptions to this increasing trend occur in rating categories where fewer bonds are observed. Further, we observe that junk-rated bonds (lower than BB) have lower average bond maturities in our sample. We now turn to the estimation of the carbon premium.

4 The carbon premium

This section describes the bond spread model and results. Our model in Section 4.1 explains the variance in credit spreads by using various bond- and firm-level spread determinants, as well as a measure of firm-level carbon emissions. In Section 4.2 we present the baseline estimation of the model. Further, in Section 4.3 we analyse the term structure of the carbon premium.

Summary statistics of sampled bonds by credit rating					
	Mean OAS	Std.dev. OAS	PD[1]	Bond maturity	No. observations:
AAA	36	23	1.4%	8.7	138
AA+	68	13	3.1%	8.8	84
AA	43	16	2.0%	7.3	396
AA-	62	27	3.2%	10.6	663
A+	79	51	3.1%	8.8	2,489
A	76	56	3.5%	10.2	5,793
A-	85	65	3.3%	12.1	13,272
BBB+	99	66	2.4%	9.7	19,953
BBB	104	79	2.5%	8.8	15,091
BBB-	153	110	3.7%	8.9	8,958
BB+	246	119	4.3%	10.4	5,219
BB	273	123	4.9%	10.1	3,742
BB-	349.8	134.0	7.7%	5.9	2,109
B+	402	133	7.7%	5.8	1,613
B	452	126	8.7%	5.1	1,075
B-	491	116	10.3%	5.3	1,148
CCC+	474	186	12.7%	4.4	320
CCC	562	42	13.9%	3.8	249
CCC-	551	141	13.3%	4.5	122
CC	591	0	29.3%	4.5	8
C	591	0	30.2%	2.9	44

Table 3: Corporate bond summary statistics by credit rating. Notably, mean yield spreads increase almost monotonically with decreasing credit rating and increasing default probability (except for categories with few observations). The probability of default is the cumulative five-year ahead probability of default, as given by Bloomberg (Bondioli et al., 2021). [1]Firm default probability is measured as the five-year cumulative probability of default as provided by Bloomberg.

4.1 The baseline model

Our model is intentionally very similar to the model introduced by Xia and Zulaica (2022). This allows us to verify the methodology and compare our results with what has been found in the US bond market. Notably, through inclusion of the variables discussed before, the model attempts to control for credit risk, liquidity risk and refinancing risk. Finally, the model controls for different bond yield dynamics across different firms, bond ratings and time by including time-, firm- and rating-fixed effects. The model we adopt, as specified by Xia and Zulaica (2022), is formalized as follows:

$$\mathrm{s}_{i,j,t} = \alpha + \beta_p P_{i,t} + \boldsymbol{\beta_Z}' \boldsymbol{Z_{i,j,t}} + \beta_{Carbon} \ln(Emissions_{i,t-12}) + \mu_i + \lambda_t + \gamma_r + \epsilon_{i,j,t}, \quad (1)$$

where:

$s_{i,j,t}$ is firm's i OAS of bond j at time t, i=1,...,N, j=1,...,M, t=1,...,T;

$P_{i,t}$ is the cumulative five-year ahead probability of default of firm i at time t;

$\boldsymbol{Z_{i,j,t}}$ is a vector of firm- and bond- specific controls at time t;

$\ln(Emissions_{i,t-12})$ is the natural logarithm of firm's i one-year lagged emissions;

μ_i is the firm-specific effect, containing one level for each of the 368 firms;[17]

γ_r is the rating-specific effect, where r is the rating of a bond at some observed time. This effect encompasses 20 credit rating levels; [18]

λ_t is the time-specific effect, containing one level for each of the 84 months;[19]

$\epsilon_{i,j,t}$ is the idiosyncratic error term.

The vector of bond- and firm-specific controls, $\boldsymbol{Z_{i,j,t}}$, contains the spread determi-

[17] Firm-specific characteristics such as leverage and firm size may affect yield spreads (Tang and Yan, 2006). Moreover, emission levels not reported by the firm, but estimated by MSCI may correlate with firm-level variables such as size and industry (Bauer et al., 2022).

[18] The bond's credit rating may amplify or reduce the effect of other variables; for lower credit ratings the unexplained variance, not explained by default risk, grows larger in absolute terms (Amato and Remolona, 2003).

[19] Time-fixed effects portray macroeconomic conditions that may influence bond yields, including the state of the yield curve and business cycle.

nants discussed in Section 3.4:

- $Duration_{j,t}$: the Macaulay duration of bond j in years at time t;
- $Age_{j,t}$: the age of bond j in years at time t;
- $Coupon_j$: the coupon of bond j in percentage points;
- $\ln(amount\text{-}outstanding_j)$: log of the amount outstanding of bond j in euro;
- $Equity\text{-}Return\text{-}Volatility_{i,t}$: the equity return volatility of firm i at time t;
- $Liquidity_{j,t}$: the liquidity of bond j in basis points at time t;
- $Callable_j$: binary variable indicating whether bond j is callable.

For estimation, we cluster standard errors at the bond level to account for serial correlation and heteroskedasticity. Use of standard errors without clustering may result in underestimated standard errors. We do not add emission levels of the two scopes as separate explanatory in one model, but rather in a separate models, as the scopes are highly correlated (Appendix A.1). We find no support for non-linearity in the specification of model 1 and hence continue without squared or cubic terms (Appendix A.2).

4.2 Baseline estimation

We conduct the estimation of Eq. 1 via a panel regression at the bond-level using ordinary least squares (OLS). Table 4 presents the results.

The carbon premium is reflected by $\hat{\beta}_{P,Carbon}$ and is significant for Scope 1 (99% confidence), Scope 2 (90% confidence) and accumulated Scope 1 and 2 emissions (99% confidence). To be concise, a 1% increase in Scope 1 carbon emissions is expected to result in a 0.05 basis point yield increment. A 1% increase in emissions over Scope 1 and 2 combined is expected to result in a 0.09 basis point yield increment.[20] These effects are substantially higher than the effects found in the US bond

[20] As the emission variable is log-transformed, the estimated effect of a 1% increase in a firm's emission level is equal to $ln(1.01)$ x $\hat{\beta}_{P,Carbon}$.

market (0.02 and 0.05, for scope 1 and scope 1 and 2 combined, respectively).[21]

A doubling of a firm's Scope 1 emissions widens the spread on the firm's issued bonds by an average of 3.64 basis points. The same doubling of a firm's Scope 1 and 2 emissions results in an average widening of bond yield spreads by 6.6 basis points. Figure 3, we visualise the estimated coefficients of each scope and the implied spread effect of a doubling in a firm's emission level.

The coefficient for Scope 2 emissions is lower and less significant, compared to the coefficient for Scope 1 emissions. This may be a result of investors considering emission levels primarily on a cumulative basis.

Turning to the control variables, we find that their impacts align with theory. The firm's probability of default is highly significant in explaining bond yields; higher default risk, logically, increases the bond yield spread to compensate for credit risk. A higher duration reflects an investor's increased exposure to interest rate risk and hence increases the bond spread. A bond's age typically relates negatively to the bond's credit risk, while relating positively to liquidity risk. We observe an average negative effect of bond age on bond spreads in our sample. As expected, a higher coupon increases the yield spread due to higher income of the investment. The outstanding amount of the bond reflects the supply available and therefore exerts downward pressure on the yield spread. Conversely, illiquidity increases the spread due to liquidity risk.

[21] In Appendix A.2 we perform a robustness test by assessing a non-linear specification of Eq. 1. We find that adding quadratic and cubic terms does not lead to significant extra explanatory power in our bond spread model.

Effects of carbon emissions on euro area corporate bond spreads

	(1)	(2)	(3)	(4)
In(Scope 1 emissions)		5.25^{***}		
		[0.93]		
In(Scope 2 emissions)			3.05^{*}	
			[1.39]	
In(Scope 1+2 emissions)				9.54^{***}
				[2.13]
Default probability (%)	3.80^{***}	3.80^{***}	3.79^{***}	3.77^{***}
	[0.37]	[0.37]	[0.37]	[0.37]
Duration	5.73^{***}	5.71^{***}	5.73^{***}	5.72^{***}
	[0.36]	[0.36]	[0.36]	[0.36]
Age	-2.45^{***}	-2.43^{***}	-2.48^{***}	-2.48^{***}
	[0.46]	[0.46]	[0.46]	[0.46]
Coupon	14.54^{***}	14.56^{***}	14.58^{***}	14.59^{***}
	[1.03]	[1.03]	[1.03]	[1.03]
In(amount outstanding)	-7.12^{***}	-7.10^{***}	-7.14^{***}	-7.16^{***}
	[1.16]	[1.16]	[1.16]	[1.16]
Equity return volatility (%)	1.97^{***}	1.97^{***}	1.99^{***}	1.96^{***}
	[0.32]	[0.32]	[0.32]	[0.31]
Illiquidity	0.14^{***}	0.14^{***}	0.14^{***}	0.14^{***}
	[0.02]	[0.02]	[0.02]	[0.02]
Callable	-16.87^{***}	-16.87^{***}	-16.95^{***}	-17.01^{***}
	[2.42]	[2.45]	[2.45]	[2.45]
Number of bonds	$1,751$	$1,751$	$1,751$	$1,751$
Observations	$82,486$	$82,486$	$82,486$	$82,486$
R-squared	0.86	0.86	0.86	0.86

Table 4: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. All OLS-specifications are with firm-, rating- and time-fixed effects. Standard errors are clustered at the bond level (ISIN) to account for heteroskedasticity and serial correlation. Sample period: January 2016 to December 2022. Sources: Refinitiv; Bloomberg; MSCI ESG. All bonds are observed monthly.

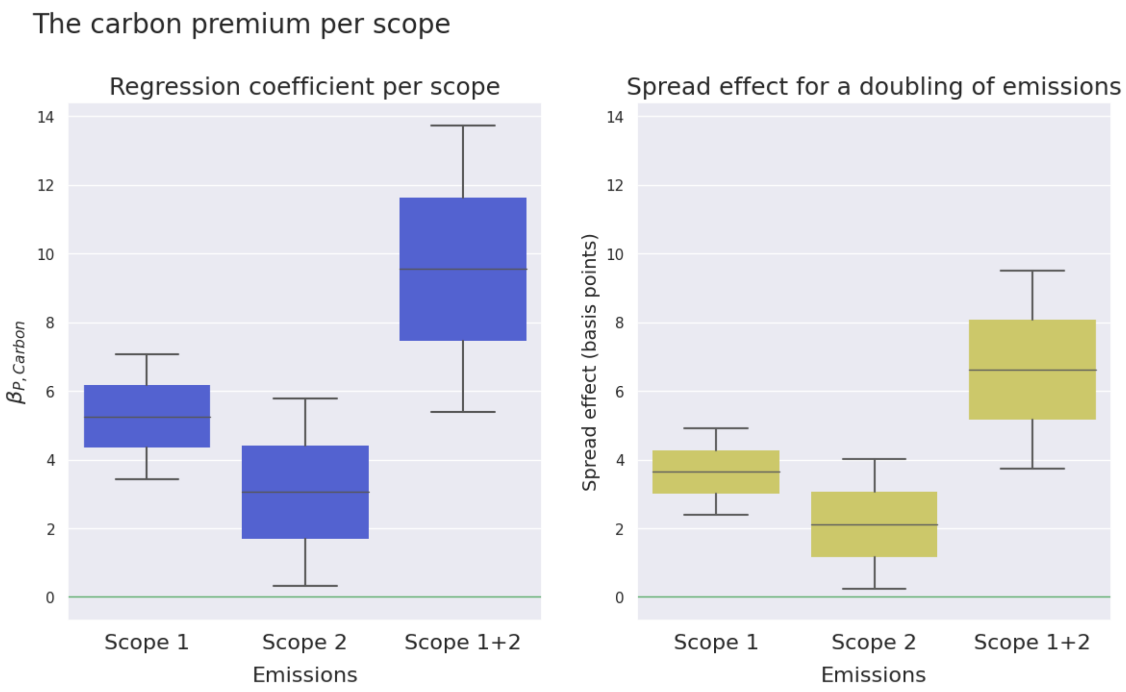

Figure 3: Confidence intervals at 95%. Left: the mean parameter coefficients and confidence intervals for Scope 1 and Scope 2 individually and for Scope 1 and 2 combined. Right: the estimated mean effect and confidence interval of a doubling of carbon emissions on the bond spread (calculated as $ln(2) * \hat{\beta}_{P,Carbon}$)

4.3 The term structure of the carbon premium

In addition, we examine whether the observed carbon premium differs depending on the maturity of the corporate bond. Xia and Zulaica (2022), for instance, find a distinctive hump-shaped term structure of the carbon premium in US corporate bonds, with the highest premia observed in bonds with 15-20 years to maturity and the least in those with under five years to maturity. The authors propose two possible explanations for this hump-shaped term structure, namely that transition risk is more of a long-term issue according to investors due to carbon pricing in legislation, and that sustainability priorities of investors vary between maturity segments depending on their investment goals.

To examine the term structure for the observed carbon premium in euro area corporate bonds, we follow the approach outlined by Xia and Zulaica (2022) and construct a variable representing bond maturity buckets, segmented in five-year increments. Subsequently, we introduce an interaction between the bucket variable and the emission variable, estimating the coefficients associated with these interaction terms.

Table 5 presents the results that indicate a significant term structure in the euro area across maturity buckets. We observe significant coefficients for the interaction terms across all scopes: emissions and maturity jointly contribute to explaining bond yields. This likely reflects the uncertainty surrounding future climate policies, which is more pronounced for the distant future. The carbon premium is noteworthy and substantial for nearly all maturities, indicating that transition risk is perceived as both a short- and long-term concern, and is consequently priced accordingly.

The carbon premium trend stabilises with increasing maturity length and does not revert. This differs from Xia and Zulaica (2022), who observed a decline in premium magnitude for bonds exceeding 20 years to maturity. Figure 1 visually depicts these dynamics across scope 1, scope 2, and combined scope 1 and 2 emissions. This persistent pattern can be attributed to the EU's definitive climate policy trajectory, which shows no signs of plateauing in the foreseeable future. This suggests that transition risk remains a significant factor in pricing, even for long-term securities. Additionally, our findings indicate that, in comparison to their counterparts in the US bond market, investors in European corporate bonds perceive transition risk as a more immediate and enduring concern.

Spread effects of carbon emissions by maturity

	(1)	(2)	(2)
Maturity < 5 years x ln(emissions)	4.25^{***}	1.36	8.60
	[0.95]	[1.36]	[2.19]
Maturity 5-10 years x ln(emissions)	5.66^{***}	2.88^{*}	10.05
	[0.93]	[1.36]	[2.17]
Maturity 10-15 years x ln(emissions)	6.54^{***}	3.91^{***}	11.00^{***}
	[0.93]	[1.37]	[2.15]
Maturity 15-20 years x ln(emissions)	7.30^{***}	4.66^{***}	11.76^{***}
	[0.95]	[1.40]	[2.15]
Maturity 20-25 years x ln(emissions)	8.22^{***}	5.79^{***}	12.70^{***}
	[0.98]	[1.44]	[2.14]
Maturity > 25 years x ln(emissions)	8.68^{***}	6.20^{***}	13.12^{***}
	[1.00]	[1.47]	[2.15]
Default probability (%)	3.86^{***}	3.86^{***}	3.83^{***}
	[0.37]	[0.38]	[0.38]
Duration	2.10^{***}	1.90^{***}	1.74^{***}
	[0.36]	[0.53]	[0.53]
Age	-2.04^{***}	-2.04^{***}	-2.09^{***}
	[0.43]	[0.43]	[0.42]
Coupon	11.83^{***}	14.58^{***}	11.71^{***}
	[0.91]	[0.91]	[0.90]
ln(amount outstanding)	-7.43^{***}	-7.54^{***}	-7.49^{***}
	[1.12]	[1.13]	[1.11]
Equity return volatility (%)	2.10^{***}	2.13^{***}	2.10^{***}
	[0.31]	[0.31]	[0.31]
Liquidity	0.13^{***}	0.13^{***}	0.13^{***}
	[0.02]	[0.02]	[0.02]
Callable	-18.48^{***}	-18.12^{***}	-18.69^{***}
	[2.35]	[2.37]	[2.32]
Number of bonds	1,751	1,751	1,751
Observations	82,373	82,373	82,373
R-squared	0.87	0.87	0.87

Table 5: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Specifications with time-, firm- and credit rating fixed effects. Standard errors are clustered at the bond level (ISIN) to account for heteroskedasticity and serial correlation. Sample period: January 2016 to December 2022. Sources: Refinitiv; Bloomberg; MSCI ESG. All bonds are observed monthly.

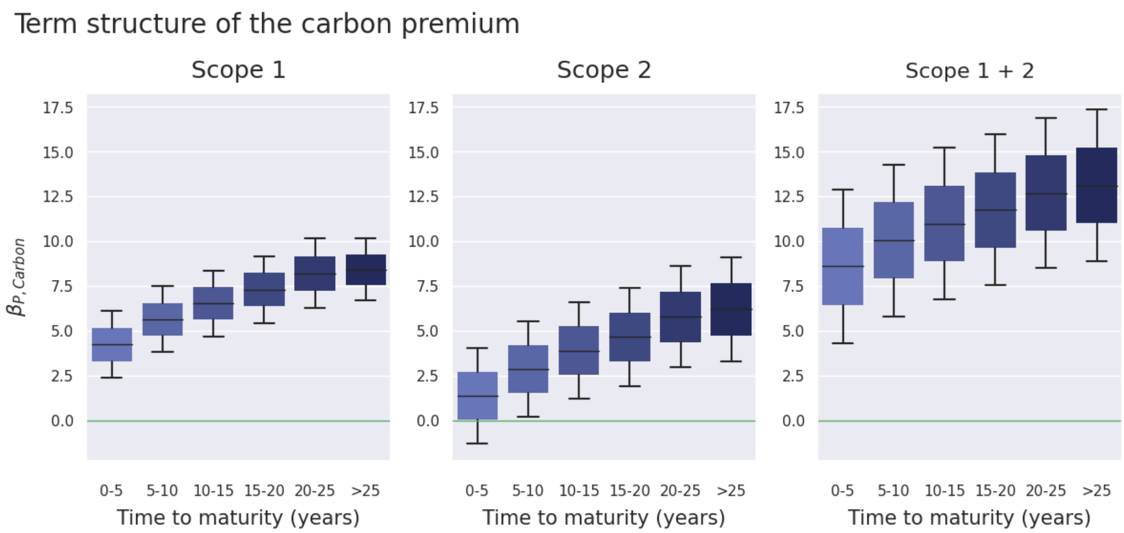

Figure 4: Term structure of the carbon preference premium over increasing maturities. Left: the term structure for Scope 1 emissions. Right: the term structure for Scope 1 and 2 combined emissions. Confidence intervals are calculated at a 95% level.

From the three figures we observe clearly that the carbon premium grows with bond maturity, with the steepest incline observed for short-term bonds. As expected, the premium is higher when we consider Scope 1 and 2 emissions together, albeit accompanied by wider confidence intervals due to the amalgamation of uncertainties.

5 The time-varying carbon premium

The carbon premium may vary over time as new information on transition risks becomes available. We therefore turn to the time-varying model to estimate how the carbon premium develops over time. In Section 5.1 we present the model and in Section 5.2 the results.

5.1 Time-varying model

We adopt an extension to the time-varying model by Li et al. (2011), who take a non-parametric local linear approach to estimate the trend and coefficient function of a panel regression with one-way fixed effects. Our original bond yield model requires the inclusion of three-way fixed effects as we control for heterogeneity across firms, bond ratings and time. When allowing for time-varying coefficients, this model reduces to a two-way fixed effects with firm- and rating fixed effects. Therefore, we redefine the matrix algebra as proposed by Li et al. (2011) so that the model can incorporate two-way or more fixed effects. The foundation of the model remains the same: we deploy a non-parametric local linear method after within-transforming the data to eliminate fixed effects.[22]

The model proposed by Li et al. (2011) relies on the knowledge that any function, given that it has continuous derivatives up to the second order, can be approximated linearly by a Taylor expansion. Hence, we first define the unknown smooth coefficient function:

$$\boldsymbol{\beta}_*(\cdot) = \boldsymbol{\beta}_*\left(\frac{t}{T}\right), \quad t = 1, \ldots, t = T,$$

so that the time input is normalised to a number between 0 and 1, and

$$\boldsymbol{\beta}_*(\cdot) = (\alpha(\cdot), \beta_P(\cdot), \boldsymbol{\beta_Z}(\cdot), \beta_{Carbon}(\cdot))^\top,$$

where $\alpha(\cdot), \beta_P(\cdot), \boldsymbol{\beta_Z}(\cdot), \beta_{Carbon}(\cdot))^\top$, are the coefficient functions over time from Eq. 1.

Then, the regression coefficient function at any time t, $\boldsymbol{\beta_*(t)}$, can be approximated linearly using the coefficients, $\boldsymbol{\beta_*(\cdot)}$, at some time τ and the derivatives of $\boldsymbol{\beta_*(\cdot)}$ at time τ:

$$\boldsymbol{\beta}_*(t) = \boldsymbol{\beta}_*(\tau) + \boldsymbol{\beta'}(\tau)(t-\tau) + O\left((t-\tau)^2\right) \tag{2}$$

where $0 < \tau < 1$. and $\boldsymbol{\beta'_*(\cdot)}$ is the derivative of $\boldsymbol{\beta_*(\cdot)}$.

Given this notion, we can approximate every observation, i.e. any observed

[22] The within transformation eliminates fixed effects by demeaning the data on the fixed effects axes. The demeaning matrix is given by $\boldsymbol{Q_D = I - D_f(D_f' D_f)^{-1} D_f'}$, where $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{D_f}$ the matrix of firm-, rating- and time-fixed effects.

bond spread, in our sample $\boldsymbol{s}' = \left\{\boldsymbol{s_{11t_1}}, \boldsymbol{s_{12t_2}}, \dots, \boldsymbol{s_{2jt_j}}, \dots, \boldsymbol{s_{NMt_M}}\right\}$ in a similar manner. However, the firm-, time-, and rating-fixed effects from Eq. 1 - μ_i, λ_t and $\gamma_{j,t}$, respectively - pose a challenge for this representation. Therefore, we gather the regressors from Eq. 1 in the design matrix $\boldsymbol{X}$ and within-transform the regressors gathered in $\boldsymbol{X}$ and the spreads gathered in $\boldsymbol{y}$. Now, instead of taking cross-sectional averages as proposed by Li et al. (2011) for one-way effects, we apply the within transformation to the design matrix, so that $\tilde{\boldsymbol{X}}$ holds the demeaned design matrix $\tilde{\boldsymbol{X}} = \boldsymbol{X}\boldsymbol{Q_D}$, with demeaning matrix $\boldsymbol{Q_D}$ Then, we have that:

$$\mathrm{s}_{i,j,t} \approx \boldsymbol{\beta}(\tau)\tilde{\boldsymbol{X}}_{i,j,t} + \boldsymbol{\beta'}(\tau)(t-\tau)\tilde{\boldsymbol{X}}_{i,j,t}, \tag{3}$$

Following Li et al. (2011), we then define a new design matrix:

$$\tilde{\boldsymbol{D}}(\boldsymbol{\tau}) = \begin{pmatrix} 1 & \tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{11t_{1,0}}} & \dfrac{t_{1,0}-\tau T}{Th} & \dfrac{t_{1,0}-\tau T}{Th}\tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{11t_{1,0}}} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{11t_1}} & \dfrac{t_1-\tau T}{Th} & \dfrac{t_1-\tau T}{Th}\tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{11t_1}} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{NMt_{M,0}}} & \dfrac{t_{M,0}-\tau T}{Th} & \dfrac{t_{M,0}-\tau T}{Th}\tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{NMt_{M,0}}} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{NMt_M}} & \dfrac{t_M-\tau T}{Th} & \dfrac{t_M-\tau T}{Th}\tilde{\boldsymbol{X}}^{\top}_{\boldsymbol{NMt_M}} \end{pmatrix} \tag{4}$$

where $t_{1,0}$ is the first month and t_1 the last month in which bond 1 is observed. Consequently, all observations can be approximated linearly using $\tilde{\boldsymbol{D}}(\tau)$, the coefficient function $\boldsymbol{\beta}_*(\cdot)$ evaluated at time τ and the derivative of function $\boldsymbol{\beta_*}(\cdot)$ evaluated at time τ:

$$\boldsymbol{s} \approx \tilde{\boldsymbol{D}}(\tau) \begin{bmatrix} \boldsymbol{\beta}_*(\tau) \\ \boldsymbol{\beta}'_*(\tau) \end{bmatrix}$$

Subsequently, we will estimate the coefficients by minimising the error of this approximation. However, when approximating time τ, the error of all bond spreads observed at time τ should bear more weight compared to bond spreads observed many months removed from time τ. Hence, we define the weight matrix:

$$\boldsymbol{W}(\tau) = \text{diag}\left(K\left(\frac{1-\tau T}{Th}\right), \ldots, K\left(\frac{T-\tau T}{Th}\right)\right), \tag{5}$$

with Lipschitz continuous kernel function $K(\cdot)$ and bandwidth h. We select a bandwidth of 18 months, after cross-validation of multiple possible choices (see Appendix B.1) and use the Triweight function as kernel (Appendix B.2):

$$K(u) = \frac{35}{32}(1-u^2)^3 \text{ for } |u| \leq 1 \text{ and } 0 \text{ otherwise.} \tag{6}$$

Finally, the OLS minimisation task is formulated as: (**?**)

$$\arg \min_{\substack{\boldsymbol{\beta_*(\tau)}\in\mathbb{R}^{d+1}, \\ \boldsymbol{\beta_*(\tau)}'^{\top}\in\mathbb{R}^{d+1}}} \left(\tilde{\boldsymbol{s}} - \tilde{\boldsymbol{D}}(\tau) \begin{bmatrix} \boldsymbol{\beta_*(\tau)} \\ \boldsymbol{\beta'_*(\tau)} \end{bmatrix}\right)^{\top} \boldsymbol{W}(\tau) \left(\tilde{\boldsymbol{s}} - \tilde{\boldsymbol{D}}(\tau) \begin{bmatrix} \boldsymbol{\beta_*(\tau)} \\ \boldsymbol{\beta_*(\tau)'} \end{bmatrix}\right) \tag{7}$$

So that we obtain the coefficients at time τ:

$$\hat{\boldsymbol{\beta}}_*(\tau) = [\boldsymbol{I}_{d+1}, \boldsymbol{0}_{d+1}][\tilde{\boldsymbol{D}}^{\top}(\tau)\boldsymbol{W}(\tau)\tilde{\boldsymbol{D}}(\tau)]^{-1}\tilde{\boldsymbol{D}}^{\top}(\tau)\boldsymbol{W}(\tau)\tilde{\boldsymbol{s}} \tag{8}$$

5.2 Time-varying results

Figure 5 displays the time-varying coefficients for $\hat{\beta}_{Carbon}$ across scope 1, 2, and both scopes combined. This figure illustrates the impact across different maturity buckets through distinct curves. For clarity, only the mean estimates are depicted, omitting multiple confidence intervals to avoid clutter and enhance interpretation of the results.

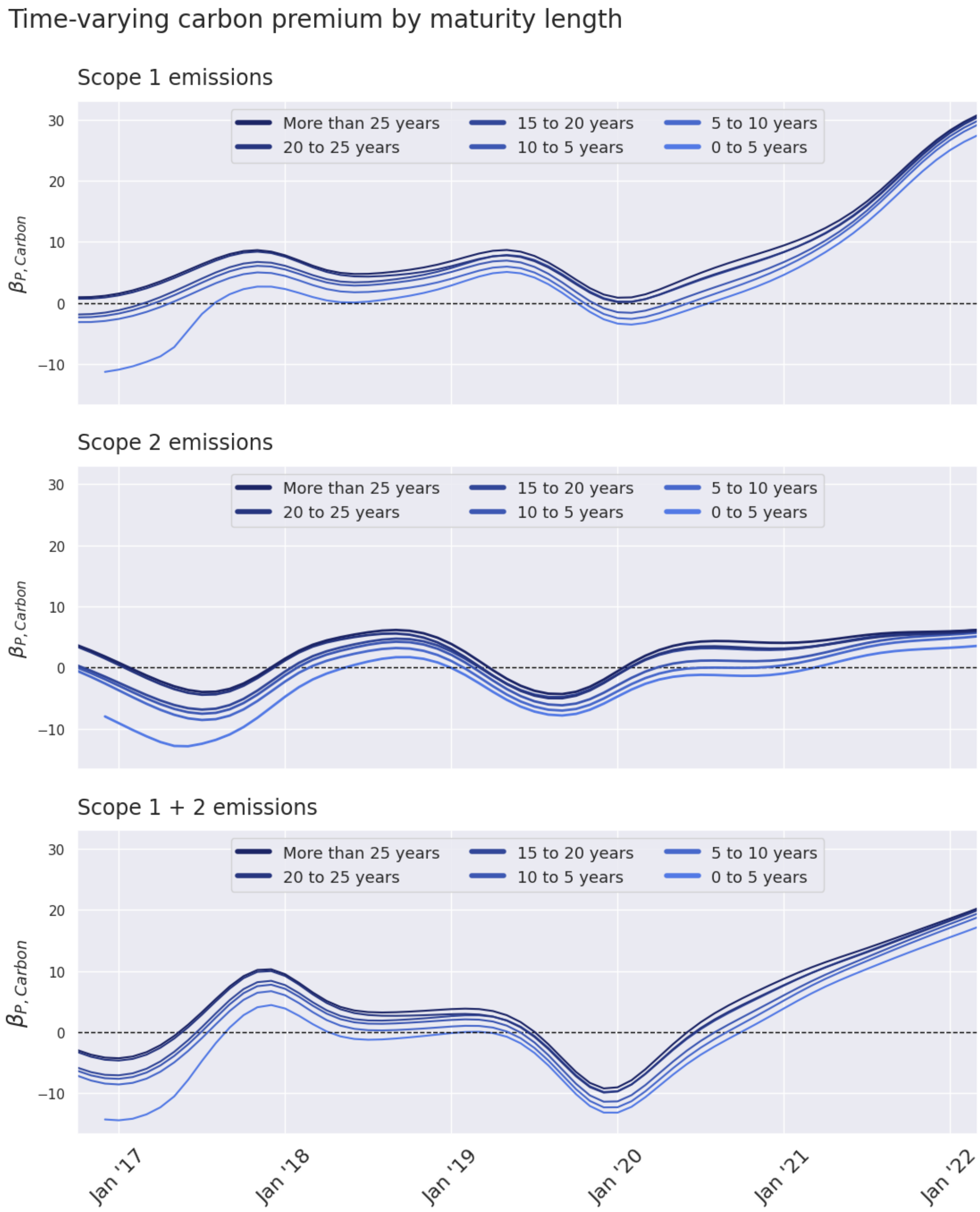

Figure 5: Term structure of the carbon preference premium by scope; darker colours represent longer maturity lengths and vice versa; the premium has been steadily rising from mid 2020, after being negative or insignificant for years. Confidence intervals are excluded to ease visual interpretation of the term structure.

Figure 5 shows that a substantial rise in the carbon premium starts to occur in early 2020 for both Scope 1 and Scope 2 emissions. In 2020, the carbon premium for Scope 1 emissions increase from near 0 to approximately 30 by early 2022. At the same time, the carbon premium for Scope 2 emissions also exhibits an increase, albeit to a lesser degree. A potential explanation for the increase in Scope 1 and Scope 2 emission premiums may be that the pricing of transition risk is largely anchored to the EU's carbon emission allowance prices at the time. Intuitively, a firm's short-term transition risk is predominantly driven by emission expenditures. Although the cap-and-trade system, under which carbon allowances are issued, has been in place since 2007, carbon permit prices began to rise substantially from March 2020 onwards. However, disentangling the carbon permit price from broader climate policies enacted from early 2020, such as the introduction of the Carbon Border Adjustment Mechanism (CBAM) and European climate law, poses challenges. Moreover, climate litigation has started to target firms since the case *Milieudefensie et al. v. Shell* in 2021, which was the first case to successfully hold a firm accountable for climate damages. This is another form of climate transition risk urging investors to price a carbon premium.

Figure 6 positions the curve of the EU carbon allowance price above the time-varying carbon premium over all maturities for Scope 1 emissions. Although further research is necessary in order to establish any causal relationship, our attention is drawn to the break of both curves in early 2020, where both the carbon permit price and the carbon premium start to rise steadily.

We also note a gradual flattening of the term structure of the carbon premium. While the shortest-term maturity (0 to 5 years) maintains a slight separation from the rest, all other buckets practically converge to the same premium by early 2022. The increasing trend in the premium over maturity length, as depicted in Figure 4, seems to be losing strength over the years. This observation suggests that the anticipated materialisation of transition risk is expected to be relatively consistent today and in several years. Consequently, the premium on bonds maturing in ten

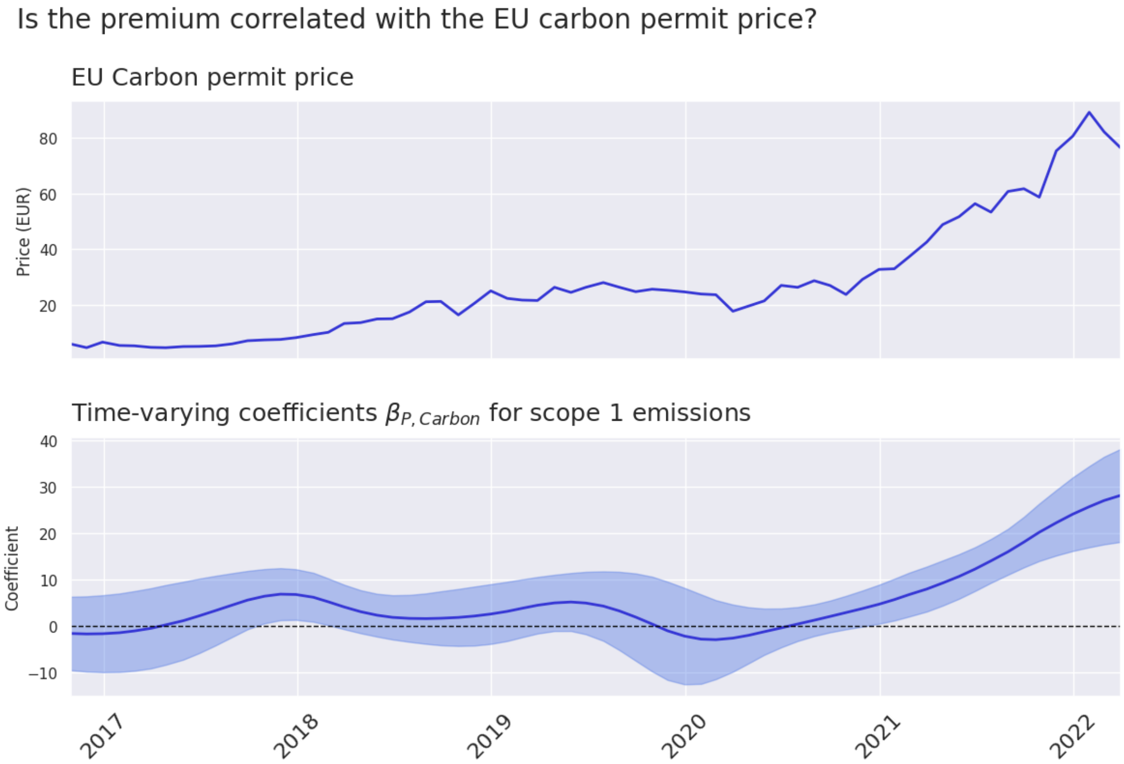

Figure 6: Upper: Carbon permit price for emissions covered under the EU ETS cap-and-trade system. Lower: the carbon premium coefficients for Scope 1 emissions over all maturity lengths. Data points are observed on a monthly base. Source: Bloomberg.

years is roughly equal to that for bonds maturing in twenty years. This conjecture implies two assumptions: first, investors anticipate a relatively certain progression of carbon pricing within the EU; second, this pricing is expected to progress in tandem with the risk-free rate, resulting in similar perceived pricing today and in twenty years.

This may seem counterintuitive at first, considering that both scopes exhibit positive and significant pricing. However, as illustrated in Figure 2, a firm's average level of Scope 2 emissions typically exceeds that of Scope 1 emissions. Consequently, a 1% reduction in a firm's total emissions is likely to be more reflective of a decrease in Scope 2 emissions. Given that the carbon premium for Scope 1 emissions is significantly higher than for Scope 2, the aggregated impact on the bond spreads could be less pronounced than that of Scope 1 emissions alone.

6 Conclusions

We present evidence of the existence of a significant carbon premium in euro area corporate bonds, which has steadily increased since early 2020. Over the whole sample period, from 2016 to 2022, we observe that a doubling of a firm's Scope 1 and 2 emissions on average implies 6.6 basis point higher bond yield spreads. This pricing of transition risks appears to be more prevalent in the euro area than in the US (Xia and Zulaica, 2022). Notably, the carbon premium emerged strongly in early 2020, after being negative or negligible for several years. From early 2020, the carbon premium increases steadily so that the effect more recently, in early 2022, is substantially higher than the sample average. A doubling of Scope 1 and Scope 2 emissions by early 2022 on average results in a higher spread of 13.9 basis points. This means that European firms with high levels of carbon emissions face increasingly high financing costs.

Our research also reveals a distinctive carbon premium term structure, rising with longer maturities. This increase suggests that investors anticipate either increasingly strict climate regulations or heightened uncertainty about future climate policies and carbon emission pricing. Note that this term structure flattens over time, so that the premium between short-term and long-term maturity bonds has diminished in recent years. The carbon premium for buckets containing the 20-25 year and longer maturities converge; only the premium in very short-term maturities (less than five years) is visibly distinguishable from other maturities. This finding stands in contrast to the US, where a hump-shaped term structure is found that is steeply rising for short-term maturities and declining for maturities longer than 20 years (Xia and Zulaica, 2022). We conjecture that the flattening term structure indicates investors' perception of a reasonably certain, progressive trajectory in the EU's climate policy. This trajectory advances at such a pace such that pricing today is as challenging as pricing, say, twenty years from now.

Our findings highlight, to some extent, why various studies have come to conflicting conclusions on the presence and magnitude of a carbon premium in financial asset prices. We show that the choice of sample period is an important determinant of the presence and extent of a carbon premium. Various developments may have lead to the emergence of a significant carbon premium in early 2020 and its subsequent rise until 2022. We observe substantial similarity in the path of the carbon premium and that of the EU carbon allowance price for emissions covered under the EU Emission Trading System (EU ETS). Additionally, we illustrate how climate litigation has become an important frontier of transition risk in the last years, which may have urged investors to progressively price a carbon premium.

We believe the results offer opportunities for future research. First, our study suggests that future research should aim to establish whether a causal relationship exists between the EU's carbon price and the carbon premium. In addition, it is valuable to assess the effect of the carbon premium at a corporate level. To what extent do increased financing costs pose threats to the viability of certain companies, or what other implications could arise?

References

Alessi, L., Ossola, E., and Panzica, R. (2019). The greenium matters: Evidence on the pricing of climate risk. *University of Milan Bicocca Department of Economics, Management and Statistics Working Paper*, (418).

Amato, J. D. and Remolona, E. M. (2003). The credit spread puzzle. *BIS Quarterly Review, December.*

Aswani, J., Raghunandan, A., and Rajgopal, S. (2023). Are carbon emissions associated with stock returns? *Review of Finance, forthcoming.*

Bai, J., Bali, T. G., and Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, 131(3):619–642.

Bali, T. G., Subrahmanyam, A., and Wen, Q. (2021). The macroeconomic uncertainty premium in the corporate bond market. *Journal of Financial and Quantitative Analysis*, 56(5):1653–1678.

Bats, J., Bua, G., and Kapp, D. (2023). Physical and transition risk premiums in euro area corporate bond markets. Working Paper 761, De Nederlandsche Bank.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4):283–288.

Bauer, M. D., Huber, D., Rudebusch, G. D., and Wilms, O. (2022). Where is the carbon premium? global performance of green and brown stocks. *Journal of Climate Finance*, 1:100006.

Bernardini, E., Di Giampaolo, J., Faiella, I., and Poli, R. (2021). The impact of carbon risk on stock returns: evidence from the european electric utilities. *Journal of Sustainable Finance & Investment*, 11(1):1–26.

Blasberg, A., Kiesel, R., and Taschini, L. (2021). Climate default swap—disentangling the exposure to transition risk through cds. *Available at SSRN 3856993*.

Boermans, M., Bun, M., and Van der Straten, Y. (2024). Funding the fittest? pricing of climate transition risk in the corporate bond market. Working Paper 797, De Nederlandsche Bank.

Boliari, N. and Topyan, K. (2022). Holding companies and debt financing: A comparative analysis using option-adjusted spreads. *Journal of Risk and Financial Management*, 15(12):569.

Bolton, P., Despres, M., Da Silva, L. A. P., Samama, F., Svartzman, R., et al. (2020). The green swan. *Central Banking and Financial Stability in the Age of Climate Change*.

Bolton, P. and Kacperczyk, M. (2021a). Do investors care about carbon risk? *Journal of financial economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2021b). Global pricing of carbon-transition risk. Working Paper 28510, National Bureau of Economic Research.

Bolton, P. and Kacperczyk, M. (2023). Are carbon emissions associated with stock returns? comment. *Review of Finance*, page rfad019.

Bolton, P. and Kacperczyk, M. T. (2020). Carbon premium around the world.

Bondioli, M., Goldberg, M., Hu, N., Li, C., Maalaoui, O., and Stein, H. J. (2021). The bloomberg corporate default risk model (drsk) for public firms. *Available at SSRN 3911300*.

Broeders, D., Schouten, B., Tiems, I., and Verhoeven, N. (2023). Pricing of climate transition risks across different financial markets. *Journal of Risk Management in Financial Institutions*, 16(2):102–115.

Brown, M. J. and Watkins, T. (2015). The "green premium" for environmentally certified homes: a meta-analysis and exploration. *Research Gate Working Paper*.

Campbell, J. Y. and Shiller, R. J. (1991). Yield spreads and interest rate movements: A bird's eye view. *The Review of Economic Studies*, 58(3):495–514.

Campiglio, E. and der Ploeg, R. v. (2021). Macro-financial transition risks in the fight against global warming. *Available at SSRN 3862256*.

Capasso, G., Gianfrate, G., and Spinelli, M. (2020). Climate change and credit risk. *Journal of Cleaner Production*, 266:121634.

Dell'Anna, F. and Bottero, M. (2021). Green premium in buildings: Evidence from the real estate market of singapore. *Journal of Cleaner Production*, 286:125327.

Fabozzi, F. J. (2007). *Fixed income analysis*, volume 6. John Wiley & Sons.

Foerster, S. R. and Sapp, S. G. (2005). Valuation of financial versus non-financial firms: a global perspective. *Journal of International Financial Markets, Institutions and Money*, 15(1):1–20.

Gerlagh, R., Heijmans, R. J., and Rosendahl, K. E. (2022). Shifting concerns for the eu ets: are carbon prices becoming too high? *Environmental Research Letters*, 17(5):054018.

Giglio, S., Kelly, B., and Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, 13:15–36.

Greene, W. H. (2012). Econometric analysis. 7th (international) ed. new york university. *Pearson. ISBN*, 13:978–0.

Han, S. and Zhou, H. (2007). Nondefault bond spread and market trading liquidity. In *Federal Reserve Board Working Paper*.

Helwege, J., Huang, J.-Z., and Wang, Y. (2014). Liquidity effects in corporate bond spreads. *Journal of Banking & Finance*, 45:105–116.

Hilscher, J. and Wilson, M. (2017). Credit ratings and credit risk: Is one measure enough? *Management science*, 63(10):3414–3437.

Huij, J., Laurs, D., Stork, P. A., and Zwinkels, R. C. (2022). Carbon beta: A market-based measure of climate risk. *Available at SSRN 3957900.*

In, S. Y., Park, K. Y., and Monk, A. (2017). Is "being green" rewarded in the market? an empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics (Singapore Issue)*, 46(48).

Kabir, M. N., Rahman, S., Rahman, M. A., and Anwar, M. (2021). Carbon emissions and default risk: International evidence from firm-level data. *Economic Modelling*, 103:105617.

Koeman, N., Konijn, S., Pel, S., Lensink, A., and van den Burg, E. (2023).

Li, D., Chen, J., and Gao, J. (2011). Non-parametric time-varying coefficient panel data models with fixed effects. *The Econometrics Journal*, 14(3):387–408.

Livingston, M. and Zhou, L. (2002). The impact of rule 144a debt offerings upon bond yields and underwriter fees. *Financial Management*, pages 5–27.

Loyson, P., van Wijnbergen, S., et al. (2023). The pricing of climate transition risk in europe's equity market.

Lu, C.-W., Chen, T.-K., and Liao, H.-H. (2010). Information uncertainty, information asymmetry and corporate bond yield spreads. *Journal of Banking & Finance*, 34(9):2265–2279.

Lutz, B. J., Pigorsch, U., and Rotfuß, W. (2013). Nonlinearity in cap-and-trade systems: The eua price and its fundamentals. *Energy Economics*, 40:222–232.

Monasterolo, I. and de Angelis, L. (2018). Are financial markets pricing carbon risks after the paris agreement? an assessment of low-carbon and carbon-intensive stock market indices. Technical report, Mimeo. Vienna University of Economics and Business.

Monasterolo, I. and De Angelis, L. (2020). Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics*, 170:106571.

MSCI (2020). Climate data and metrics. Technical report, ESG Research LLC. Available at: https://www.msci.com/documents/1296102/16985724/MSCI-ClimateDataMetrics-Feb2020.pdf.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571.

Peel, J. and Osofsky, H. M. (2020). Climate change litigation. *Annual Review of Law and Social Science*, 16:21–38.

Roncoroni, A., Battiston, S., Escobar-Farfán, L. O., and Martinez-Jaramillo, S. (2021). Climate risk and financial stability in the network of banks and investment funds. *Journal of Financial Stability*, 54:100870.

Setzer, J. and Higham, C. (2022). Global trends in climate change litigation: 2022 snapshot.

Tang, D. Y. and Yan, H. (2006). Macroeconomic conditions, firm characteristics, and credit spreads. *Journal of Financial Services Research*, 29:177–210.

Tuckman, B. and Serrat, A. (2022). *Fixed income securities: tools for today's markets*. John Wiley & Sons.

Witkowski, P., Adamczyk, A., and Franek, S. (2021). Does carbon risk matter? evidence of carbon premium in eu energy-intensive companies. *Energies*, 14(7):1855.

Xia, D. and Zulaica, O. (2022). The term structure of carbon premia. Working Paper 1045, BIS.

Correlation of the regressors

	log Scope 1	log Scope 2	log Scope 1+2	Default Probability	Duration	Age	Coupon	log(amount outstanding)	Equity return volatility	Illiquidity	Callable
log(Scope 1)	1.00	0.58	0.93	-0.08	0.21	0.12	0.10	0.12	0.07	0.05	-0.18
log(Scope 2)	0.58	1.00	0.75	-0.11	0.15	-0.00	-0.05	0.12	0.03	-0.02	-0.09
log(Scope 1+2)	0.93	0.75	1.00	-0.10	0.23	0.11	0.08	0.11	0.07	0.04	-0.21
Default Probability	-0.08	-0.11	-0.10	1.00	-0.14	-0.05	0.17	-0.03	0.30	0.22	0.06
Duration	0.21	0.15	0.23	-0.14	1.00	-0.04	0.06	-0.04	0.11	0.32	-0.08
Age	0.12	-0.00	0.11	-0.05	-0.04	1.00	0.52	-0.27	-0.06	0.08	-0.48
Coupon	0.10	-0.05	0.08	0.17	0.06	0.52	1.00	-0.20	0.08	0.32	-0.31
log(amount outstanding)	0.12	0.12	0.11	-0.03	-0.04	-0.27	-0.20	1.00	-0.00	-0.11	0.23
Equity return volatility	0.07	0.03	0.07	0.30	0.11	-0.06	0.08	-0.00	1.00	0.25	0.02
Illiquidity	0.05	-0.02	0.04	0.22	0.32	0.08	0.32	-0.11	0.25	1.00	-0.07
Callable	-0.18	-0.09	-0.21	0.06	-0.08	-0.48	-0.31	0.23	0.02	-0.07	1.00

Table 6: This table shows the correlation coefficients of the explanatory variables included in Eq. 1. Correlations above 0.5 are displayed in red; perfect collinear pairs are displayed in blue on the diagonal and other correlations are displayed in green. Scope 1 and 2 emissions are highly correlated.

A Time-constant model validity

A.1 Correlation of the explanatory variables

Near perfect collinearity poses a problem for the estimation through inflation of the coefficients' standard errors. Hence, the confidence intervals are wider, making it more difficult to find significant effects, even though the R^2 measure of the model is high (Greene, 2012). Moreover, small changes in the data can cause large changes in the coefficient estimates when variables are near (Greene, 2012). Table 6 displays the correlation between the regressors from Eq. 1. Clearly, scope 1 and scope 2 emissions should not be included in one model as separate variables; this would lead to high collinearity affecting precisely those coefficients we are interested in. Aggregating scope 1 and scope 2 emissions into one new variable is beneficial though.

A.2 Ramsey RESET test for nonlinearity

To test for non-linearity we conduct the Ramsey RESET test. First, we fit the original model from Eq. 1, again using the package 'reghdfe' in Stata. From the fitted values, we create the square and cubic term of these values. These terms are added to the original model, so that we obtain:

$$\mathrm{s}_{i,j,t} = \alpha + \beta_{p,t}P_{j,t} + \beta_{Z,t}Z_{i,j,t} + \beta_{Carbon,t}\ln(Emissions_{j,t-12}) + \beta_{squared}\hat{s}^2_{i,j,t} +$$

$$\beta_{cubic}\hat{s}^3_{i,j,t} + \mu_j + \lambda_{i,t} + \gamma_t + \epsilon_{i,j,t}$$

We now have two models: one restricted model where we impose $\beta_{square} = \beta_{cubic} = 0$ and one unrestricted model where quadratic or cubic variables may explain the variance in the spread data. Then, we calculate the F-statistic:

$$F = \frac{(SSR_R - SSR_{UR})/p}{SSR_{UR}/(N-p-1)}$$

$$= \frac{(SSR_R - SSR_{UR})/2}{SSR_{UR}/(1314-2-1)} = 1.52$$

The p-value of the F-statistic having a value of 1.52 for an F(2,1314) distribution is 0.2183. Hence, we do not reject the null hypothesis of correct specification. We find that adding quadratic and cubic terms do not lead to a significant extra explanatory power in our bond spread model.

B Time-varying model validity

B.1 Bandwidth cross-validation

The bandwidth determines the range in which observations away from the time τ contribute to the evalutation of the coefficient function at time τ. If the bandwidth is set too small, the model is overly sensitive to noise in the data; if it is set too large, the model overgeneralizes.

We use K-fold cross-validation to choose the best bandwidth in a range of tested values. We partition the data set into k subsets, or 'folds'. We estimate the model k times, each time using $k-1$ folds for estimation and the remaining fold for validation.

We repeat this process k times, where each subset is used exactly once as validation data.

The minimization criterion for the optimal model is the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{9}$$

where n represents the number of observations in the validation set, Y_i is the actual observation, and $\hat{Y}_i$ is the predicted observation. Therefore, the bandwidth selection criterion can be formally defined as

$$\hat{h} = \underset{h \in H}{\operatorname{argmin}}\ MSE(h) \tag{10}$$

where $\hat{h}$ is the optimal bandwidth, H is the set of possible bandwidths, and $MSE(h)$ is the mean squared error of the model with bandwidth h. This approach to bandwidth selection ensures that we select the model that best fits our data in terms of minimizing the prediction error. We first conduct cross-validation within the bandwidth space $H = [10, 14, 18, 22, 26]$ and then apply a narrower cross-validation around the chosen optimal bandwidth from the previous set of bandwidths. Table 7 displays the cross-validation results. A bandwidth of 18 months yields the best results: hence, we choose this value for the estimation of our time-varying bond yield spread model.

B.2 Kernel selection

Results of a time-varying kernel model are relatively robust to various kernel choices, but confidence intervals are more spiky and outlier-sensitive for finite support kernels. We use the Triweight kernel, consisting of a sixth-order equation. This function has infinite support on a compact set; this is a desirable property for both outlier robustness and asymptotic properties. Additionally, this kernel has a high sensitiv-

	Grid 1		Grid 2
Bandwidth	**MSE**	**Bandwidth**	**MSE**
10	45,446.49	16	23,483.85
14	14,249.01	17	18,483.85
18	**13,728.99**	**18**	**13,728.99**
22	13,940.25	19	17,452.10
26	23,120.12	20	21,755.89

Table 7: Mean Squared Error (MSE) for various bandwidth values in the cross-validation process. Grid 2 is the narrowed grid search around the optimal bandwidth from grid 1. The lowest MSE is obtained when fixing the bandwidth on 18 months.

ity, meaning that more weight is given to data points close to the target point and relatively little weight to data points far away.

$$K(u) = \frac{35}{32}(1 - u^2)^3 \tag{11}$$

DeNederlandscheBank
EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl