THE CARBON CONUNDRUM

INVESTIGATING THE RELATIONSHIP BETWEEN CARBON RISK AND EUROZONE CORPORATE BOND RETURNS

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Abstract:

We examine whether carbon risk, proxied by a firm's carbon emission intensity (CEI), is priced in the cross-section of the Eurozone corporate bond market. Using rolling regressions to estimate systematic risk factor loadings and then conducting panel regressions under different fixed effects combinations, we examine the varying dynamics that affect the pricing of carbon risk in the bond market. We find that bonds issued by firms with higher CEI systematically earn lower returns, indicating a mispricing at a broader level, although the economic effect is marginal at -0.1 basis points. Further investigation suggests that the pricing of carbon risk is episodic in nature and context-sensitive rather than being consistently integrated overtime in the bond market. Disruptive periods such as COVID-19 amplify the mispricing due to intensified climate concerns and shifts in investor preferences leading to lower returns for bonds of high-CEI firms relative to others. Outside such disruptions, carbon risk is priced significantly within industries. In the stable and longer run, carbon risk is priced at a more localized level, reflecting the influence of changing sectoral norms in favor of sustainability and investors' attention to their local contexts.

Keywords:

Carbon risk, corporate bonds, carbon emission intensity

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I. Introduction

According to scientific literature, climate change poses a major threat that could result in severe damage to the global economy (Burke, Hsiang and Miguel, 2015; Dietz, Bowen, Dixon and Gradwell, 2016; Lesk, Rowhani and Ramankutty, 2016). For instance, Stern (2007) projects that the annual economic cost of climate change will amount to at least 5% of annual global gross domestic product (GDP). Consensus has grown this past decade around the need for stricter government regulations and enforcement to mitigate the potential catastrophic effects of climate change. Since climate change is primarily driven by the accumulation of greenhouse gas (GHG) emissions in the atmosphere, any effective regulation would focus on decreasing companies' carbon emissions substantially. This could, for example, be done through mechanisms such as cap-and-trade programs or carbon taxes.

Policies aimed at mitigating climate change are expected to have varied impacts across the economy, with the most significant impacts likely occurring on carbon-intensive companies. As climate conditions worsen, stricter emission regulations are likely to be introduced, leading to declining values for carbon-intensive companies. Moreover, they may face increased financing costs if banks and institutional investors want to reduce their exposure to such companies because of climate-related policies that induce a shift towards sustainable investment, according to Delis, De Greiff, Iosfidi and Ongena (2024) and Krueger, Sautner and Starks (2020). We refer to the financial risks associated with owning or financing carbon-intensive assets as carbon risk. This includes exposure to regulatory changes and transition risks, such as shifts in consumer preferences toward sustainable products, technological advances, and potential reputational damage, all of which can have significant financial implications (Görgen, Jacob, Nerlinger, Riordan, Rohleder and Wilkens, 2019).

Securities issued by carbon-intensive firms are generally considered riskier because they lose value in scenarios where investors are more sensitive to climate concerns (Pástor, Stambaugh and Taylor, 2022). To compensate for their increased exposure to carbon risk, investors should demand higher expected returns, according to risk-based asset pricing theories. We refer to this as the 'carbon risk premium' hypothesis, following Duan, Li and When (2021). An alternative hypothesis, referred to as the 'investor preference' hypothesis, is that bonds of carbon-intensive firms underperform the bonds of firms with low carbon intensity because of strengthening investor preference for greener assets. This can be motivated by recent research such as Pástor et al. (2022) which

suggests that over a period when climate concerns increase more than anticipated and demand from investors with a non-pecuniary preference for green assets rises, green assets might outperform brown ones in the short run. The findings of Duan et al. (2021) support this hypothesis, as they find that bonds of more carbon-intensive firms earn significantly lower returns.

The conflicting findings in current research suggest that whether carbon risk is priced in the financial markets remains a conundrum, motivating the focus of our research. Our paper examines the pricing of carbon risk, which is proxied by a firm's carbon emission intensity (CEI) since it offers a direct quantification of climate impact, in the European corporate bond market. More specifically, we test whether the carbon risk premium hypothesis holds. We expect that the clientele of corporate bonds in Europe will take carbon risks into account and have a stronger preference for sustainable investments since Europe has embraced a proactive stance on climate change with strong regulatory frameworks and a cultural commitment to sustainability. Their non-pecuniary preference for greener assets, in our case low-CEI firms, can increase, especially over a period where climate concerns increase unexpectedly, which leads to the underperformance of firms with high CEI; in other words, more greener, low-CEI firms can outperform their high-CEI counterparts over that period, despite having lower expected returns as found by Pástor et al. (2022). Thus, we expect our results to be like those of Duan et al. (2021).

Within the European corporate bond market, our paper focuses on the Eurozone market specifically to avoid currency denomination risk and facilitate cross-country benchmarking. The countries in our sample consist of Germany, Portugal, Italy, France, Spain, Slovenia, Austria, Belgium, the Netherlands, Greece, Latvia, Luxembourg, Slovakia, Ireland, Malta, and Finland. We exclude Cyprus, Lithuania, and Estonia from the sample as they adopted the Euro in-between our sample period. Excluding these countries ensures that all countries in our sample share a fully consistent Eurozone history during the analysis period, leading to a clean and comparable dataset.

We collect bond pricing and characteristics data from Bloomberg for the period 2009-2021, and firm-level carbon emissions data from MSCI for the period 2008-2020. The bond pricing data is filtered to exclude bonds that are structured notes, mortgage-backed, asset-backed, perpetual, convertible, or trading under unusual conditions. We are focusing on Eurozone fixed-coupon bonds with greater than a year to maturity. To capture broader economic impacts, ensuring that the relationship between CEI and bond returns is isolated, we estimate time-varying factor loadings (bond market beta, default beta, term beta, illiquidity beta and

macroeconomic uncertainty beta) using rolling regressions with 24-month and 36-month windows. CEI is calculated by dividing the firm's carbon emissions (scopes 1 and 2) by its sales.

Panel regressions are used to test whether carbon risk is priced in bond returns after controlling for bond-specific characteristics and systematic risk factors. In the baseline model, the log of carbon emissions intensity (LN_CEI) shows a negative but insignificant relationship with bond returns, suggesting no systematic impact without accounting for unobserved heterogeneity. Control variables, such as downside risk and liquidity beta, are significant, aligning with our theoretical expectations. When fixed effects are included, LN_CEI becomes significant and negative under time-fixed effects, indicating that higher CEI reduces bond returns systematically over time. When we combine different fixed effects, we find LN_CEI to be insignificant under the country plus industry and country plus time fixed effects specifications but highly significant under time plus industry fixed effects. This suggests systematic market-wide mispricing. A mixed-effects model supports these findings, showing greater variability in bond returns over time than across industries, emphasizing the role of time-varying factors such as regulatory shifts, increasing climate concerns, and investor sentiment. Overall, carbon risk appears systematically mispriced in the Eurozone bond market, with high CEI linked to lower bond returns. These results align with recent literature, such as Duan et al. (2021).

We conduct further robustness checks using 36-month rolling betas. While LN_CEI remains significant under time-fixed effects, it also starts showing weaker significance under industry-fixed effects but goes on to lose significance when both are applied together, reflecting limited robustness over longer horizons. These mixed results stem from a smaller sample size, as many bonds lack sufficient return data for 36-month calculations, making interpretations less reliable. However, assuming reliability, the results suggest nuanced dynamics influencing carbon risk pricing over the long run. LN_CEI remains insignificant in baseline and country-fixed effects models but shows weak significance under time- and industry-fixed effects, hinting at localized pricing of carbon risk. We find a significant positive coefficient under country-industry fixed effects which suggests a carbon premium for high-emission firms in specific contexts, reflecting heterogeneity influenced by regional and sectoral characteristics and the investor's localized perspective. Over time, markets may adjust and price carbon risk more efficiently within certain sectors and regions.

Carbon-intensive industries are then excluded as our next robustness check to test whether our results reflect broader market trends or if they are being driven

by specific sectors. Our results stay robust for all specifications when we systematically remove energy and utility, materials, and industrials one by one and then all together, which credibly addresses the concerns that the significance of LN_CEI is driven by carbon-intensive industries. This suggests that our earlier findings are not influenced by the presence of high-emitting sectors but persist in the broader market.

Moreover, to check whether our findings are not altered by the periods of extreme market disruption during COVID-19, we exclude the year 2020 when running our regression. We find LN_CEI to be negative and significant under the baseline model, which implies market-wide mispricing of carbon risk without accounting for heterogeneity. Under country-fixed effects, LN_CEI remains insignificant, indicating that carbon risk pricing is not localized. In comparison, it becomes significant and negative with industry-fixed effects, suggesting systematic penalization of high-carbon firms within industries. Interestingly, LN_CEI becomes marginally insignificant under time-fixed effects when 2020 is excluded, contrasting with its earlier significance. This suggests that temporal shocks, such as the pandemic, amplify carbon risk mispricing, likely due to heightened investor attention on sustainability during crises. Outside periods of disruption, industries play a key role in pricing carbon risk. These findings emphasize the contingent and event-driven nature of carbon risk pricing, shaped by periods of increasing climate concerns and strengthening investor preference for sustainability during crises.

As our main results and robustness checks overall support the finding that higher LN_CEI is associated with lower future bond returns and already point towards the context-sensitivity of the mispricing, we further examine the nature of this negative relationship by testing the investor preference hypothesis. Using the Crimson Hexagon (CH) Negative Climate Change News Index created by Engle, Giglio, Kelly, Lee and Stroebel, (2020), we create the dummy variable HIGH_CHNN and interact it with LN_CEI. When combining both of their effects, we can see that bonds of high-CEI firms yield relatively lower returns when negative climate news is high. We go on to investigate the moderating effect using the Wall Street Journal (WSJ) Climate Change News Index, also constructed by Engle et al. (2020). In contrast to the first index, the interaction between our dummy variable HIGH_WSJ and LN_CEI is insignificant here. This could be because the WSJ index captures both positive and negative news. Overall, these results highlight the importance of negative news in moderating the pricing of carbon risk.

Our research makes several significant contributions to the existing strand of literature. First, we extend the discussion of carbon risk pricing from the equity market, which has been the focus of the existing literature in this field (e.g. Bolton and Kacperczyk, 2021), to the bond market. Second, our paper fills a regional gap by focusing on the Eurozone bond market instead of the U.S. market, which most research papers in this field, like Duan et al. (2021); Engle, Giglio, Kelly, Lee and Stroebel (2020) focus on. Furthermore, we take a more detailed approach to studying the evolving and time-varying dynamics of carbon risk pricing in the bond market. Our research gives insight into the complex factors that shape risk pricing in this market. Moreover, it highlights the need and acts as motivation to further investigate this underexplored market.

Our discussion would be incomplete without mentioning the data limitations. After filtering for complete cases, the number of annual observations in our dataset is reduced substantially, mainly due to the limited availability of firm-level CEI measures for all years in the time period, and the data requirements of rolling regressions, which demand a minimum time window for beta estimation. Moreover, our data is inherently unbalanced since the majority of bonds in the sample were issued toward the end of the time period. This can cause biases since bonds issued later in the sample period might be more sensitive to carbon risk as investor awareness and regulations have evolved recently. Also, our sample mainly consists of bonds from the financial sector as well as German bonds, which could create further bias in the estimates. A limitation in our methodology is that we use standard test statistics in our regressions, due to inconsistencies with alternatives like Newey-West and clustered errors, which may influence the robustness of our estimates. However, the standard t-statistics is aligned with Newey-West results, so we chose t-statistics for simplicity.

The rest of our paper is structured in the following way: In section II, we review the existing literature and develop different hypotheses as motivated by recent findings. In section III, we describe the data and construct the variables used in our empirical analysis. In section IV, we present our methodology, results and discussions. Section V concludes our paper, providing a summary of our findings in addition to a discussion of limitations and suggestions for future research.

II. Literature Review & Hypotheses Development

In this section, we present our literature review and hypotheses development. In subsection A, we offer a concise review of the relevant literature and highlight how our study contributes to the existing body of work. In subsection B, we present our hypotheses motivated by theories linking a firm's carbon risk to its expected returns.

A. Related Literature and Contribution

Our study makes several major contributions to the existing strand of literature. First, our paper extends the discussion of carbon risk beyond the equity market, bringing much-needed attention to the bond market. There is a substantial body of work examining the pricing of carbon risk in the equity market (e.g. Bansal, Wu and Yaron, 2021; Hong, Li and Xu, 2019; Bolton and Kacperczyk, 2021; Engle et al., 2020). However, limited attention has been paid to how the carbon risk of firms influences the expected returns of corporate bonds. One reason why it is of value to focus on the corporate bond market is that corporate bonds differ from equities in their risk-reward profiles, as bonds are more exposed to downside risks (Hong and Sraer, 2013), which climate policies and regulations often exacerbate for carbon-intensive firms, particularly in high-yield segments (Ilhan, Sautner and Vilkov, 2018; Hoepner, Oikonomou, Sautner, Starks and Zhou, 2024). Moreover, since debt financing is a crucial component of firms' capital structures, understanding how carbon emissions influence borrowing costs is critical. The corporate bond market's size (Goldstein, Jiang and Ng, 2017) further emphasize the policy importance of studying the relationship between carbon risk and bond pricing.

Second, our paper shifts the geographic focus from the U.S. market, which has been the subject of most research in this area, to the Eurozone corporate bond market. Closely related to our paper, Duan et al. (2021) investigate whether carbon risk is priced in the cross-section of U.S. corporate bond returns, using both a portfolio-level and bond-level approach. They find that bonds of firms with higher CEI tend to underperform, contradicting the carbon risk premium hypothesis. We recognize that the Eurozone market operates under different regulatory, economic, and environmental conditions, which may lead to unique pricing dynamics. Thus, since the dynamics are different in the Eurozone, we want insight into the relationship between CEI and corporate bond returns in this area, considering specific systematic risks inherent to the Eurozone corporate bond market. This makes our findings more relevant to investors and policymakers in this region.

Third, we provide valuable insight into the complex factors that influence risk pricing in the Eurozone corporate bond market, for instance by taking into

account liquidity premium in our analysis, inspired by Aussenegg, Goetz and Jelic (2012). Additionally, compared to, for example, Duan et al. (2021) who conduct Fama-MacBeth regressions with industry-fixed effects, our approach delves deeper into the heterogeneity that may influence the relationship between LN_CEI and future bond returns. For example, we study the differences between short-term and long-term dynamics by systematic risk betas estimated from 36-month rolling regressions. Our robustness check for COVID-19 gives us a deeper insight into how carbon risk pricing is influenced in times of disruption. This allows us to present a more nuanced perspective on the temporal dynamics of carbon risk pricing in the bond market. Moreover, our research offers a foundation and motivation for future research in this underexplored market, particularly in the Eurozone.

B. Hypotheses Development

Since carbon-intensive firms are more likely to lose value when climate policies become more stringent or customers shift to green products, investors should demand higher expected returns for holding these riskier assets, according to risk-based asset pricing theories. Theories grounded in limited risk-sharing (Merton, 1987) also suggest a positive relationship between CEI and expected returns. With a growing number of investors divesting from carbon-heavy assets, corporate bond investments in carbon-intensive companies are declining. This significant divestment leads to less risk diversification, making investors demand a higher return for holding these riskier bonds. This leads us to our first hypothesis:

H1: Carbon risk premium hypothesis: *Corporate bonds issued by firms with higher CEI are riskier and should earn higher average returns than bonds issued by firms with lower CEI.*

Although risk-based theories predict a positive carbon risk premium, the empirical relationship between CEI and bond returns could go in either direction. Pástor et al. (2022) suggest that over a period when climate concerns increase more than anticipated and demand from investors with a non-pecuniary preference for green assets rises, green assets might outperform brown ones in the short run. Duan et al. (2021) further find that bonds of firms with higher CEI consistently underperform the bonds of firms with lower CEI. More specifically, they find that the cross-sectional relationship between CEI and future bond returns is negative and highly significant. Their full model generates a negative average slope of −0.036 for LN_CEI, representing an economically significant effect of 0.12% per month. Their results align with the view that carbon risk is not fully incorporated in bond pricing, therefore implying that investors are not

appropriately compensating for the carbon risk posed by firms with higher CEI. This leads us to our alternative hypothesis:

H2: Investor preference hypothesis: *If climate concerns strengthen unexpectedly, the corporate bonds of firms with higher CEI perform worse than anticipated.*

III. Data and Variable Definitions

In this section we describe the data and variable definitions that will go into the main empirical analysis. Section A focuses on bond characteristics data and bond returns. Section B focuses on bond market systematic risk factors. Section C focuses on emission data and Section D presents a detailed discussion of our sample and summary statistics.

A. Corporate Bond Data and Bond Returns

Eurozone corporate bond pricing data is retrieved from Bloomberg covering the period 2009-2021. This period is chosen to capture post-financial crisis dynamics and incorporate relevant macroeconomic changes. To exclude bonds that do not meet our research criteria, the bond pricing data is filtered by removing bonds that are structured notes, mortgage-backed, asset-backed, perpetual, or convertible, since these securities differ significantly in risk structure and pricing. We also exclude bonds that are trading under unusual conditions, such as flat trading, from the data set to ensure reliability. We only select bonds that have greater than one year to maturity and have fixed coupon rates, as floating-rate and short-term instruments behave differently in response to market conditions, such as interest rate changes and liquidity fluctuations, which could introduce inconsistencies into our analysis. Fixed coupon rates provide stability in interest payment structures, making these bonds more suitable for assessing the impacts of long-term macroeconomic and regulatory changes. Furthermore, we only select bonds from Eurozone countries, excluding Lithuania, Cyprus and Estonia, as they adopted the Euro after 2009. Excluding these countries ensures that all countries in our sample share a fully consistent Eurozone history during the sample period, resulting in a clean and comparable dataset.

For bond pricing data, we use the last traded price of the bond for the day, sourced from Bloomberg. After we have compiled the bond pricing data, we use the bond CUSIP identifier to collect bond characteristics data from Bloomberg and then merge them together. We collect data on amount issued, amount outstanding, issue date, maturity date, coupon rate, coupon type, coupon

frequency, credit rating and issuer information such as the industry they belong to. Regarding credit ratings, we select bond credit ratings from Moody's, which are then converted into numerical values to help make the analysis straightforward. 1 refers to an AAA rating and 21 refers to a C rating, 22 D rating. A higher numerical score means higher credit risk. Numerical ratings of 10 or below, which correspond to BBB- or better, are considered investment grade, and ratings of 11 or higher, corresponding to BB + or worse, are labeled high yield. Additionally, we assign a value of zero to unrated bonds.

We calculate the monthly return for each bond i in month t by first calculating the dirty price of the bond by first adding accrued interest to the end-of-month clean price, then dividing it by previous months' dirty price and subtracting one at the end. The excess bond return is calculated by subtracting the risk-free rate, which is proxied by the one-month EURIBOR[1] rate.

B. Bond Market Systematic Risk Factors

We also compute the systematic risk factors linked to the corporate bond market, specifically in Europe, to estimate the time-varying factor loadings which will then be used as control variables for the main panel regressions. This helps us consider economic factors that determine the cross-section of corporate bond returns in the Eurozone, hence giving us a clearer analysis of the relationship between a firm's CEI and its corporate bond returns.

We use the excess corporate bond market return, the term spread, the default spread and macroeconomic uncertainty to proxy for bond market risk factors. We calculate the bond market excess returns for the Eurozone market (EXCESS_BMKT_RETURN) as the difference between the bond market monthly returns and our risk-free rate proxy, the 1-month EURIBOR rate. The index used as a benchmark for the bond market return is the Bloomberg Euro Aggregate Corporate Total Return index. This index gives comprehensive coverage while being consistent with our research focus on Eurozone corporate bonds. The 1-month EURIBOR rate is chosen as it is well aligned with the scope of our analysis, reflects short-term, low-risk borrowing costs, and is widely accepted in financial research and practice.

Next, the default spread (DEFAULT_SPREAD) is measured as the difference between BAA and AAA-rated corporate bond monthly yields. We include this factor because bonds with higher credit risk are more vulnerable to financial instability. The term spread (TERM_SPREAD) is computed as the difference

[1] This has been taken from Eurostat

between the monthly return on the ICE BofA 10+ Euro Government Index and the EURIBOR 1-month rate. This allows us to capture the sensitivity of bond returns to changes in the term structure of interest rates, as longer-term bonds are more sensitive to interest rate changes. De Vette and Mosk's (2022) study highlights the significance of these spreads in analyzing financial stability and the pricing of corporate bonds in the Eurozone.

To proxy for a bond's exposure to broad economic uncertainties (MACRO_UNC), we use the Global Uncertainty Index (GUI)[2] to account for macroeconomic uncertainty, recognizing the Eurozone's sensitivity to global economic conditions due to its integration into international markets. Events like the 2008 global financial crisis demonstrate how global uncertainty affects regional economies, impacting bond markets.

In addition to these common risk factors, we consider factors that are especially relevant for the European bond market. For instance, Houweling, Mentink and Vorst (2005); Diaz and Navarro (2002); Frühwirth, Schneider and Sögner (2010) find a liquidity premium for European corporate bonds in their sample. Illiquidity is a critical factor since bonds that are harder to trade generally demand a premium, impacting their returns. To proxy for the market illiquidity (MARKET_ILLIQUIDITY), we subtract the EURIBOR 1-month rate from the 1-month EONIA rate[3] following Aussenegg et al. (2012).

We estimate the time-varying betas for every bond *i* in month *t* using rolling regressions. We use betas estimated by rolling windows of 24 months, which provides a balanced view, capturing both short-term fluctuations and medium-term trends, to model each bond's exposure to the systematic risk factors that we previously introduced:

$$
\begin{aligned}
EXCESS_RETURN_{i,t} \\
&= \alpha_{i,t} + \beta^{MARKET} EXCESS_BMKT_RETURN_t \\
&+ \beta^{ILLIQ} MARKET_ILLIQUIDITY_t + \beta^{TERM} TERM_SPREAD_t \\
&+ \beta^{DEFAULT} DEFAULT_SPREAD_t + \beta^{MACRO} MACRO_UNC_t + \varepsilon_{i,t}
\end{aligned}
$$

Where $\beta_{MKT,i,t}$ is the bond market beta, $\beta_{DEF,\,i,t}$ is the default beta, $\beta_{TERM,\,i,t}$ the term beta, $\beta_{UNC,\,i,t}$ is the macroeconomic uncertainty beta and $\beta_{ILLIQ,\,i,t}$ is the market illiquidity beta. The betas have been scaled in order to normalize their magnitudes and the differences in their scales.

[2] The index is freely available at http://www.policyuncertainty.com/

[3] This can be found on ECB Data Portal

C. Emission Data

Firm-level carbon emission data for Eurozone corporations from 2008-2020 is sourced from MSCI. The reason why we use this time period is to establish a lag between the predictor (CEI) and the future excess bond returns. Our collected carbon emissions data consists of direct emissions from owned or controlled facilities by the company (that is, scope 1 emissions) and emissions from purchased heat, steam, and electricity (that is, scope 2 emissions), measured in metric tons/million EUR. We use scope 1 and scope 2 emissions as they are more observable and reported than scope 3 emissions, so investors can rely more on scope 1 and 2. We construct CEI from scratch since MSCI currently has carbon emission intensities expressed in metric tons/million USD. We calculate it as a firm's carbon emissions (scope 1 and 2) divided by its sales in EUR, taken from Bloomberg, to construct the CEI measure in metric tons/million EUR. For further regression analysis, the emissions data is log-transformed to address skewness.

D. Sample and Summary Statistics

We begin with a comprehensive set of monthly pricing data for 8,493 unique bonds and create our main dataset for analysis by first cleaning the pricing data. Bonds with trading histories of less than 6 months are excluded to ensure the reliability of our return estimates. We then compute monthly excess returns and subsequently annualize them to align with the temporal structure of CEI, which is available as an annual measure. All other explanatory variables, like monthly beta estimates, have been annualized for this reason as well.

To construct the firm-level CEI measure, we gather a time series of carbon emissions for firms remaining in the sample after the pricing data is cleaned. We combine our main variables of interest with control variables like scaled betas, lagged returns, downside risk and others critical for explaining bond returns. After filtering for complete cases, the dataset is reduced to 3,457 annual observations for 1,463 unique bonds when using annualized betas estimated via 24-month rolling regressions. The sample size diminishes further when 36-month rolling regressions are employed in one of our robustness checks.

The main factors driving this substantial decrease in our sample are the limited availability of firm-level CEI measures for all years in the period and the data requirements of rolling regressions, which demand a minimum time window for beta estimation. Alternative methods such as a GARCH-BEKK model (Pieterse-Bloem et al., 2016) could be used to estimate unconstrained betas without losing data for the window size but it requires a much longer time series, typically 20 to

40 years of data, to be able to produce any estimates. Consequently, we proceed with the rolling regression method which provides a practical balance between data requirements and estimation flexibility. Second, the lack of consistent carbon emissions disclosures across the sample period may itself be pointing towards uneven pricing of carbon risk over time in our sample. Despite this, the reporting improves towards the end of our sample period reflecting the growing importance of this factor. Nevertheless, even though such cleaning of data leads to a substantial shrinking of the sample size, avoiding missing values is important to obtaining reliable estimates.

Moreover, it is also important to note that our data is inherently unbalanced, as most bonds in the sample were issued toward the end of the time period. This characteristic of our data has important implications for further analysis since it can cause potential biases as bonds issued later in the sample period might reflect heightened sensitivity to carbon risk as investor awareness and regulations would have evolved in recent years. The bonds predominantly belong to Germany and the financial sector. This may potentially be another source of bias in our estimates due to the limited geographic and sectoral diversity. For instance, one may expect the carbon risk to not be significantly priced in the financial sector. These characteristics constrain the analysis and can point towards the need to control for such time, industry, and country-specific factors in our main model.

Table 1 reports summary statistics for the key variables used in our baseline analysis. Over our sample period, the average annual return on the corporate bonds is 0.82% with a standard deviation of 0.053. This shows that the returns do not vary as much, which may be due to homogeneous bond market characteristics within the Eurozone. Our main independent variable, LN_CEI, has a mean of 5.26 metric tons per million Euros approximately[4] and a standard deviation of 8.94 metric tons per million Euros, showing some variance. An average bond has a rating of 2.6 (which can be interpreted as an Aa2 Moody's rating) and has 10.97 years to maturity. All of the betas exhibit positive means , except Beta_UNC which shows a slightly negative mean, and all have quite low variances, while, for example, maturity and rating_score show significant ranges. The VIF tests conducted on the data do not show any serious multicollinearity issues between our explanatory variables.

[4] $e^{1.66} \approx 5.26$. Same is done for standard deviation.

TABLE 1: SUMMARY STATISTICS

Table 1 reports summary statistics for annual bond observations over the sample period from January 2009 to December 2021. The descriptive statistics include the sample mean, 25th percentile, median, 75th percentile and standard deviation of the key variables used in this study. Variables are defined in the Appendix, Table A1.

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
Excess_Return_Next_Year	0.0083	-0.0254	-0.0017	0.0363	0.0533
LN_CEI	1.6660	-0.0687	1.3755	2.5266	2.1993
VAR	0.0246	0.0142	0.0200	0.0295	0.0174
rating_score	2.6107	0.0000	1.0000	5.0000	3.2435
Maturity	10.9726	7.0000	9.0000	13.0000	5.7967
log_amt_outstanding	17.8027	16.5236	17.7275	19.3370	1.8768
Beta_BMKT	0.0091	0.0046	0.0082	0.0130	0.0089
Beta_DEFAULT	0.0043	0.0003	0.0063	0.0103	0.0125
Beta_TERM	0.0032	-0.0007	0.0018	0.0058	0.0074
Beta_UNC	-0.0006	-0.0022	-0.0002	0.0012	0.0043
Beta_ILLIQ	0.0200	0.0041	0.0155	0.0318	0.0318

IV. Empirical Results

In this section we describe our methodology and present as well as discuss our results. Subsection A considers bond-level panel regressions while subsection B focuses on robustness checks, and in section C we test the investor preference hypothesis.

A. Bond-Level Panel Regressions

To examine the cross-sectional relationship between CEI and future bond returns, Fama-Macbeth regressions are widely used (e.g. Duan et al., 2021). However, according to Petersen (2007), panel regressions with fixed effects enable researchers to enhance the efficiency of estimates. Like Huyhn and Xia (2020), we thus choose to use bond-level panel regressions. This approach is ideal for handling panel data with multiple time periods, enabling us to estimate average coefficients. The model is specified as follows:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot LN(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} \, CONTROLS_{k,t} + \epsilon_{i,t+1}$$

where $R_{i,t+1}$ (Excess Return) is the future excess return on bond in year t +1 and $LN_CEI_{i,t}$ is the natural logarithm of firm-level CEI in the previous year *t*. $CONTROLS_{k,t}$ include bond-level characteristics and systematic risk factors. Bond-level characteristics include downside risk (VAR), which represents the 5% Value-at-Risk of corporate bond return. To ensure consistency, the rolling window for calculating VAR matches the rolling window used for estimating betas. For example, if 24-month windows are used for the regressions, the same 24-month window is applied for VAR calculations. We define VAR as the second lowest monthly return observation over the rolling window and multiply it by −1. A higher VAR is interpreted as a higher downside risk. Downside risk is included because it captures extreme negative outcomes, which are essential when assessing the risks faced by bondholders in times of financial stress. Another bond-level characteristic we use is credit ratings (rating_score) to represent the bond's risk level. Furthermore, we use time to maturity (Maturity), the natural logarithm of bond's outstanding amount in EUR (log_amt_outstanding), and one-month lagged bond return (Lagged_Return). Moreover, the factor loadings estimated in section III are included to capture the covariance between corporate bond returns and the relevant systematic risk factors. We exclude firm-level characteristics from our analysis motivated by Huynh and Xia's (2020) findings that their results do not qualitatively change if they do not control for firm-level characteristics, such as market capitalization, Tobin's Q, ROE and leverage ratio.

To choose between random or fixed effects, we conduct the Hausman test, which shows us that the fixed effects model is preferred over random effects. After finding significance for the Hausman test, we proceed to test the relationship between LN_CEI of a firm and the future excess returns of its corporate bonds using various fixed-effects specifications. The choice of the fixed effects is made based on how much variation in our main variable of interest, LN_CEI, is explained by them. Unlike Huyhn and Xia (2020), who apply bond fixed effects when investigating the relationship between a bond's climate change news beta and future returns, we find that LN_CEI varies little within our bonds which makes them unsuitable to control for in our analysis as they would likely absorb most of the variation in LN_CEI. However, we find substantial variation in LN_CEI across countries and industries which motivates our choice to include country and industry fixed effects. We further control for time-fixed effects based on an ANOVA test, which reveals highly significant variation over time for our main independent variable. The results of applying different combinations of fixed effects reveal interesting insights into how carbon risks are priced into the cross-section of bond returns in our sample.

In the baseline model in the first column of Tabel 2, panel A, without any fixed effects, we see a negative but statistically insignificant relationship between LN_CEI and future bond excess returns. The control variables included in the regression, such as the downside risk and the default and term beta, are highly significant which aligns with our theoretical expectations of these variables based on previous research (Bai, Bali and Wen, 2019; Pieterse-Bloem et al., 2016). The liquidity beta also shows significance, giving support to the findings of Aussenegg, Goetz and Jelic (2012), Houweling et al. (2005), Diaz and Navarro (2002) and Frühwirth et al. (2010). Moreover, the presence of significance for the intercept suggests that there are other omitted variables that contribute to explaining the corporate bond returns. The result shows that a firm's carbon emissions intensity is not a significant determinant of bond returns when we do not account for unobserved heterogeneity.

However, as we start applying different fixed effects one at a time, not only does the direction of the relationship change, but the significance also changes. When we apply industry-fixed effects (Table 2, Panel A, column 3), the coefficient remains insignificant with a negative sign. This means that within-industry differences in the carbon emissions intensity do not explain the bond pricing. We get similar statistically insignificant results when we apply country-fixed effects (Table 2, Panel A, column 2), but with a small positive coefficient, which implies that within-country differences do not account for carbon risk substantially as well. Together, they tell us that carbon risk is not significantly priced within a specific country or industry and hence is not localized. However, when we control for time-varying factors (Table 2, Panel A, column 4), LN_CEI becomes highly statistically significant at 1% and shows a negative relationship with future bond excess returns (coefficient = -0.001). This shows that, after accounting for time-specific factors like changes in regulations and environmental concerns, higher CEI consistently leads to lower bond returns over time. In economic terms, a coefficient of -0.001 implies that a 1% increase in CEI reduces annual future excess bond returns by approximately -0.001% or -0.1 basis points (bps) [5] relative to the mean. The negative effect, although it seems small, may accumulate over time and/or as carbon-intensive firms continue to be careless about their emissions. For example, if a firm increases its CEI by 10%, it will see a decrease in its annual bond excess returns by around -1 basis point. A doubling of its CEI would reduce returns by approximately -6.93 basis points annually. This finding rejects our first hypothesis that carbon risk is efficiently priced according to traditional risk pricing theories and aligns with the findings of the closely related

[5] A 1% increase in the original CEI corresponds to a change in log CEI of approximately 0.00995.

TABLE 2: PANEL REGRESSIONS WITH 24 MONTH ESTIMATED BETAS

This table reports the average intercept and slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of fixed effects. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panel A shows the estimates (1) without any fixed effects, under (2) country, (3) industry and (4) time fixed effects. Panel B shows the estimates under (1) country plus time, (2) industry plus time and (3) country plus industry fixed effects. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel A: Individual Fixed Effects Models

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.0004	0.0003	-0.001	-0.001***
	(0.0004)	(0.0005)	(0.001)	(0.0003)
VAR	0.420***	0.397***	0.429***	0.426***
	(0.063)	(0.064)	(0.064)	(0.050)
rating_score	0.001**	0.001**	0.001**	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Maturity	0.002***	0.002***	0.002***	0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
log_amt_outstanding	0.001***	0.001**	0.001*	0.001**
	(0.0005)	(0.001)	(0.001)	(0.0004)
Lagged_Return	-0.242***	-0.241***	-0.241***	-0.170***
	(0.012)	(0.012)	(0.012)	(0.013)
Beta_BMKT	-0.278**	-0.262**	-0.282**	0.039
	(0.130)	(0.131)	(0.132)	(0.101)
Beta_DEFAULT	-0.978***	-1.010***	-1.002***	-0.294***
	(0.081)	(0.083)	(0.082)	(0.062)
Beta_TERM	-2.313***	-2.386***	-2.371***	-0.776***
	(0.173)	(0.177)	(0.176)	(0.136)
Beta_UNC	-1.451***	-1.544***	-1.474***	-0.275
	(0.217)	(0.223)	(0.219)	(0.170)
Beta_ILLIQ	0.086***	0.085***	0.092***	-0.002
	(0.029)	(0.029)	(0.029)	(0.022)
Constant	-0.028***			
	(0.009)			
Observations	3,427	3,427	3,427	3,427
R^2	0.223	0.229	0.226	0.578
Adjusted R^2	0.220	0.224	0.221	0.576
Residual Std. Error	0.047 (df = 3415)	0.047 (df = 3404)	0.047 (df = 3405)	0.035 (df = 3406)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: Combined Fixed Effects Models

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.0003	-0.001***	0.001
	(0.0004)	(0.0005)	(0.001)
VAR	0.389***	0.423***	0.406***
	(0.051)	(0.051)	(0.065)
rating_score	0.0005**	0.0005**	0.001**
	(0.0002)	(0.0002)	(0.0003)
Maturity	0.001***	0.0004***	0.002***
	(0.0001)	(0.0001)	(0.0002)
log_amt_outstanding	0.0004	0.001*	0.001
	(0.0004)	(0.0004)	(0.001)
Lagged_Return	-0.165***	-0.171***	-0.240***
	(0.013)	(0.013)	(0.012)
Beta_BMKT	0.046	0.035	-0.281**
	(0.101)	(0.102)	(0.133)
Beta_DEFAULT	-0.301***	-0.302***	-1.026***
	(0.063)	(0.063)	(0.084)
Beta_TERM	-0.848***	-0.796***	-2.452***
	(0.139)	(0.139)	(0.181)
Beta_UNC	-0.380**	-0.309*	-1.538***
	(0.174)	(0.172)	(0.225)
Beta_ILLIQ	-0.010	0.003	0.089***
	(0.022)	(0.022)	(0.029)
Observations	3,427	3,427	3,427
R^2	0.587	0.580	0.231
Adjusted R^2	0.583	0.576	0.224
Residual Std. Error	0.034 (df = 3395)	0.035 (df = 3396)	0.047 (df = 3394)
Note:			*p<0.1; **p<0.05; ***p<0.01

research of Duan et al. (2021). As the CEI of a firm increases, the returns on its bonds decrease instead of the investors being compensated, in the form of higher returns, for holding the higher risk. This can suggest that investors might be systematically mispricing carbon risk. Bringing together insights from these combinations of fixed effects, we can conclude that carbon risk is systematically priced inefficiently at a broader market-wide level.

Next, we test combinations of fixed effects shown in Table 2, Panel B. We avoid applying all factors together to avoid overfitting data. First, LN_CEI remains insignificant for country plus industry and country plus time combinations (Table 2, Panel B, column 1 and 3, respectively), which builds on our argument that carbon risk pricing is not driven by local, country- or industry-related contexts. A plausible reason for this could be that countries in our sample all belong to the Eurozone and have similar policies, even though they can still have differences in investor attitudes among others. Moving on, the coefficient for LN_CEI is negative and highly significant under time plus industry fixed effects (Table 2, Panel B, column 2). This implies that the Eurozone corporate bond market displays systematic mispricing on a broader market level and penalizes firms with high CEI when industry-related factors interact with time-related ones and that industries can serve as a channel for (mis)pricing of carbon risk. This could be because of a shift in broader sectoral norms. We explore this notion further using a mixed effects model (Appendix, Table A2) which shows similar estimates and significance levels but gives additional insight through variance decomposition (Appendix, Table A3) which shows that bond returns exhibit greater variability over time than across industries, as evidenced by larger random-effect variance for time. This highlights the greater influence of time-related dynamics (Pástor et al., 2022), for instance, regulatory shifts or investor sentiment changes, compared to industry-specific factors in driving bond pricing. Since both fixed and mixed models have a similar fit, we proceed with the fixed-effects model for further analysis.

Our results show that carbon risk is systematically mispriced over time in the Eurozone bond market at a market-wide level and is potentially influenced by time-varying dynamics. The conclusion made above may face certain risks due to low data quality or small sample coverage, as discussed before. However, we see robust significance for other control variables, which may suggest that the regression models are generally well-specified. Moreover, we use standard test statistics in our regressions, which may influence the robustness of the significance of our estimates. The reason for continuing with the standard test statistics was the lack of robustness between different methods, such as Newey-West and clustered standard errors. This obviously stems from the underlying

issue they try to correct. After accounting for heterogeneity, clustered standard errors may over-control by inflating standard errors in smaller samples or when there is insufficient variability within clusters. During initial tests, Newey-West standard errors quantitatively give similar results to the standard test statistics, and hence, for simplicity, we chose to use them in our regressions. A better and more thorough selection of standard errors may increase the reliability of our results. Lastly, the regressions will benefit from additional control variables, to mitigate omitted variable bias, increased sample size and improved data quality to reliably estimate the exact relationship between carbon emissions intensity and bond returns.

B. Robustness Checks

To ensure the robustness of our findings, we perform various robustness checks across different dimensions. These robustness checks ensure that our findings are reliable and can be generalized across various market conditions, bond characteristics, and economic periods.

B.1. Different Rolling Regression Window

When checking for robustness of our findings with 36-month rolling betas, we find significance for LN_CEI when applying time-fixed effects (Table 3, Panel A, column 4), consistent with our previous results. Interestingly, industry-fixed effects (Table 3, Panel A, column 3) also show some significance and a positive relationship for LN_CEI. This time, LN_CEI loses its significance when applying both industry plus time fixed effects (Table 3, Panel B, column 2). One of the reasons behind the lack of statistical robustness of our results when using 36-month betas could be that our sample consists mostly of bonds that were issued towards the end of our period of interest. Hence, there is not sufficient return data to compute reliable 36-month betas and this leads to a much smaller sample of bonds with complete cases, which affects the robustness of our results.

Alternatively, assuming estimates are reliable, it could give us insight into the difference between the short-term and longer-term relationship between LN_CEI and future excess bond returns. In the baseline and country-fixed effects model (Table 3, Panel A, column 1 and 2, respectively), LN_CEI continues to be insignificant. The intercept also becomes less significant in the baseline regression which can imply that our model includes most of the variables which explain the bond excess returns in the long run. After controlling for industry and time-fixed effects separately (Table 3, Panel B, column 3 and 4, respectively), we see a weak significance for the relationship between CEI and the future excess bond returns. This means that carbon risk might be priced within industries and

across time while not being dependent on country-specific contexts, but the evidence for it is weak.

Here, the country plus time and industry plus time fixed effects combinations (Table 3, Panel B, column 1 and 2, respectively) do not show any significance. This can indicate that when looking at the market dynamics in a slightly longer-term setting, carbon risk is not systematically priced across time. However, LN_CEI becomes positive and significant under country plus industry fixed effects (Table 3, Panel B, column 3) with a slightly higher economic effect. The positive coefficient means that there is a carbon premium for bonds of high CEI firms within specific industries and countries and that markets price in the carbon risk efficiently. This implies that there is heterogeneity in how countries and industries price carbon risks in the long run and, in contrast to our analysis with 24-month betas, points towards the importance of local factors when it comes to carbon risk pricing in the long run. It suggests that carbon risk pricing, rather than being persistent overtime, operates within specific contexts shaped by more localized and sectoral dynamics. It is expected that investors naturally pay attention more to their local contexts. Moreover, although its plausibility may be argued, a reason for the premium can be that markets tend to correct any efficiencies in the longer term.

The difference in our results could mainly be attributed to the use of 36-month betas which smooths out the effects of large-scale shocks by incorporating a longer historical data period in their estimation. The longer window gives more stable estimates of systematic risk factors effectively giving us insight into longer-term dynamics where the fluctuations in the market are smoothened out. We continue with further analysis using 24-month rolling betas due to the larger sample space it offers.

B.2. Excluding Carbon-Intensive Industries

Our results, shown in Table 4, stay robust for all specifications when we systematically remove energy and utility, materials, and industrials one by one and then all together to address the concern that the significance of LN_CEI is driven by carbon-intensive industries. This suggests that our earlier findings are not influenced by the presence of high-emitting sectors but persist in the broader market.

TABLE 3: PANEL REGRESSIONS WITH 36 MONTH ESTIMATED BETAS

This table reports the average intercept and slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of fixed effects. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 36 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panel A shows the estimates (1) without any fixed effects, under (2) country, (3) industry and (4) time fixed effects. Panel B shows the estimates under (1) country plus time, (2) industry plus time and (3) country plus industry fixed effects. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel A: Individual Fixed Effects Models

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	0.00004	0.001	0.002*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.0004)
VAR	0.591***	0.580***	0.624***	0.361***
	(0.068)	(0.069)	(0.069)	(0.055)
rating_score	0.001**	0.001**	0.001***	0.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Maturity	0.001***	0.001***	0.001***	0.0003**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
log_amt_outstanding	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.0005)
Lagged_Return	-0.302***	-0.301***	-0.300***	-0.200***
	(0.017)	(0.017)	(0.017)	(0.018)
Beta_BMKT	-0.638***	-0.663***	-0.695***	-0.003
	(0.190)	(0.193)	(0.193)	(0.148)
Beta_DEFAULT	-0.016	-0.016	-0.030	-0.024
	(0.126)	(0.130)	(0.128)	(0.098)
Beta_TERM	-1.013***	-1.166***	-1.123***	0.040
	(0.268)	(0.277)	(0.273)	(0.209)
Beta_UNC	1.451***	1.420***	1.620***	1.738***
	(0.333)	(0.340)	(0.339)	(0.262)
Beta_ILLIQ	-0.178***	-0.185***	-0.190***	-0.020
	(0.049)	(0.050)	(0.051)	(0.039)
Constant	-0.021*			
	(0.012)			
Observations	2,074	2,074	2,074	2,074
R^2	0.238	0.243	0.243	0.563
Adjusted R^2	0.234	0.236	0.235	0.559
Residual Std. Error	0.047 (df = 2062)	0.047 (df = 2052)	0.047 (df = 2052)	0.036 (df = 2054)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: Combined Fixed Effects Models

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.0003	0.0002	0.003***
	(0.0005)	(0.001)	(0.001)
VAR	0.332***	0.379***	0.611***
	(0.055)	(0.056)	(0.070)
rating_score	0.001***	0.001***	0.001***
	(0.0003)	(0.0003)	(0.0004)
Maturity	0.0005***	0.0003**	0.001***
	(0.0002)	(0.0002)	(0.0002)
log_amt_outstanding	-0.0001	0.0004	0.0004
	(0.001)	(0.001)	(0.001)
Lagged_Return	-0.195***	-0.199***	-0.298***
	(0.018)	(0.018)	(0.017)
Beta_BMKT	-0.001	-0.039	-0.727***
	(0.150)	(0.150)	(0.195)
Beta_DEFAULT	-0.052	-0.039	-0.038
	(0.099)	(0.099)	(0.131)
Beta_TERM	-0.064	-0.022	-1.305***
	(0.215)	(0.214)	(0.284)
Beta_UNC	1.581***	1.834***	1.599***
	(0.266)	(0.267)	(0.346)
Beta_ILLIQ	-0.033	-0.026	-0.204***
	(0.039)	(0.040)	(0.051)
Observations	2,074	2,074	2,074
R^2	0.572	0.565	0.250
Adjusted R^2	0.566	0.559	0.238
Residual Std. Error	0.035 (df = 2044)	0.036 (df = 2044)	0.047 (df = 2042)
Note:			*p<0.1; **p<0.05; ***p<0.01

TABLE 4: EXCLUDING CARBON-INTENSIVE INDUSTRIES

This table reports the slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of fixed effects. Energy & utilities and industrials have been removed from the sample. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panels to the left show the estimates (1) without any fixed effects, under (2) country, (3) industry and (4) time fixed effects. Panels to the right show the estimates under (1) country plus time, (2) industry plus time and (3) country plus industry fixed effects. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel A.1: Individual Fixed Eff. Excluding Energy and Utility

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.001	0.0001	-0.001	-0.001**
	(0.001)	(0.001)	(0.001)	(0.0004)
Observations	3,122	3,122	3,122	3,122
R^2	0.248	0.255	0.251	0.575
Adjusted R^2	0.245	0.250	0.246	0.572
Residual Std. Error	0.045 (df = 3110)	0.045 (df = 3100)	0.045 (df = 3102)	0.034 (df = 3101)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel A.2: Combined Fixed Eff. Excluding Energy and Utility

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.0005	-0.001***	0.0002
	(0.0004)	(0.0005)	(0.001)
Observations	3,122	3,122	3,122
R^2	0.585	0.577	0.257
Adjusted R^2	0.581	0.573	0.250
Residual Std. Error	0.034 (df = 3091)	0.034 (df = 3093)	0.045 (df = 3092)
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel B.1: Individual Fixed Eff. Excluding Industrials

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.0004	0.0003	-0.001	-0.001***
	(0.0004)	(0.0005)	(0.001)	(0.0003)
Observations	3,346	3,346	3,346	3,346
R^2	0.221	0.227	0.224	0.581
Adjusted R^2	0.219	0.222	0.219	0.578
Residual Std. Error	0.047 (df = 3334)	0.047 (df = 3323)	0.047 (df = 3325)	0.035 (df = 3325)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B.2: Combined Fixed Eff. Excluding Industrials

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.0003	-0.001**	0.001
	(0.0004)	(0.0005)	(0.001)
Observations	3,346	3,346	3,346
R^2	0.590	0.582	0.229
Adjusted R^2	0.586	0.579	0.222
Residual Std. Error	0.034 (df = 3314)	0.035 (df = 3316)	0.047 (df = 3314)
Note:			*p<0.1; **p<0.05; ***p<0.01

TABLE 4: EXCLUDING CARBON-INTENSIVE INDUSTRIES (CONTINUED)

This table reports slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of fixed effects. Materials and then all of the carbon intensive industries are removed from the sample. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panels to the left show the estimates (1) without any fixed effects, under (2) country, (3) industry and (4) time fixed effects. Panels to the right show the estimates under (1) country plus time, (2) industry plus time and (3) country plus industry fixed effects. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel C.1: Individual Fixed Eff. Excluding Materials

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.0003	0.0004	-0.001	-0.001***
	(0.0004)	(0.0005)	(0.001)	(0.0003)
Observations	3,367	3,367	3,367	3,367
R^2	0.211	0.217	0.214	0.578
Adjusted R^2	0.209	0.212	0.209	0.576
Residual Std. Error	0.047 (df = 3355)	0.047 (df = 3344)	0.047 (df = 3346)	0.034 (df = 3346)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel C.2: Combined Fixed Eff. Excluding Materials

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.0003	-0.001**	0.001
	(0.0004)	(0.0005)	(0.001)
Observations	3,367	3,367	3,367
R^2	0.588	0.580	0.220
Adjusted R^2	0.584	0.576	0.213
Residual Std. Error	0.034 (df = 3335)	0.034 (df = 3337)	0.047 (df = 3335)
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel D.1: Individual Fixed Eff. Excluding All Carbon Intensive Ind.

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.001	0.0003	-0.001	-0.001**
	(0.001)	(0.001)	(0.001)	(0.0004)
Observations	2,981	2,981	2,981	2,981
R^2	0.232	0.240	0.235	0.577
Adjusted R^2	0.229	0.235	0.231	0.574
Residual Std. Error	0.045 (df = 2969)	0.045 (df = 2960)	0.045 (df = 2963)	0.034 (df = 2960)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel D.2: Combined Fixed Eff. Excluding All Carbon Intensive Ind.

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.001	-0.001***	0.0004
	(0.0005)	(0.0005)	(0.001)
Observations	2,981	2,981	2,981
R^2	0.588	0.579	0.242
Adjusted R^2	0.584	0.575	0.235
Residual Std. Error	0.033 (df = 2951)	0.034 (df = 2954)	0.045 (df = 2954)
Note:			*p<0.1; **p<0.05; ***p<0.01

B.3. Removing the Effects of COVID-19

Motivated by our second hypothesis that the systematic pricing of carbon risk may be driven by periods of increasing climate concern, we test the robustness of our results by excluding the period during which COVID-19 caused large-scale disruptions in financial markets while also increasing climate concerns. This could have affected the pricing of carbon risks in corporate bonds. We exclude the year 2020 from our sample to investigate how removing a year where climate concerns are strengthened affects the relationship between LN_CEI and bond excess returns. The baseline model (Table 5, Panel A, column 1) reveals a negative and significant coefficient for LN_CEI which suggests a broader mispricing of carbon risk in the market without accounting for potential heterogeneity. The insignificance of LN_CEI after applying country-fixed effects (Table 5, Panel A, column 2) suggests that the pricing of carbon risk has not been localized to country-specific factors even outside major disruptions, indicating a more market-wide pricing of carbon risk, which is consistent with our previous conclusion.

However, when we control for industry-fixed effects (Table 5, Panel A, column 3), LN_CEI becomes negative and significant, which means that bonds of firms with higher CEI within industries have been earning lower returns. This implies that there has been systematic mispricing and penalization of carbon-intensive firms within industries and implies that industries can serve as another key channel for carbon risk pricing outside periods of large-scale disruption and intensified climate concerns. This reflects the fact that investors focus more on sector-specific carbon risks and incorporate them into pricing compared to broader, market-wide temporal factors in the absence of such disruptions. In contrast, when we included COVID-19 in our sample earlier, industry-specific pricing became insignificant, likely because the pandemic introduced overlapping shocks that blurred industry-specific pricing. Investors most likely shifted their attention to broader risks and immediate economic uncertainties and climate concerns which reduced the focus on sector-level carbon risks. The fact that LN_CEI becomes marginally significant when we apply time-fixed effects after removing the pandemic gives more nuance to this argument (Table 5, Panel A, column 4). After comparing the result to the initial significance of LN_CEI under time-fixed effects (Table 2, Panel A, column 3), we can conclude that major market shocks and large-scale intensification of climate concerns amplify the mispricing of carbon risk where bonds of firms with high CEI earn lower returns, possibly due to shifts in investors nonpecuniary preferences aligning with the expectations of our second hypothesis and findings of Pástor et al. (2022), indicating that investor demand for greener assets play a critical role in these periods.

TABLE 5: REMOVING THE EFFECTS OF COVID-19

This table reports the slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of fixed effects. The year 2020 is removed from the sample as a proxy for Covid-19. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panel A shows the estimates (1) without any fixed effects, under (2) country, (3) industry and (4) time fixed effects. Panel B shows the estimates under (1) country plus time, (2) industry plus time and (3) country plus industry fixed effects. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel A: Individual Fixed Effects Models

	Dependent variable:			
	EXCESS RETURNS			
	(1)	(2)	(3)	(4)
LN_CEI	-0.002***	-0.0004	-0.002**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.0004)
Observations	1,971	1,971	1,971	1,971
R^2	0.157	0.170	0.164	0.514
Adjusted R^2	0.152	0.161	0.155	0.509
Residual Std. Error	0.049 (df = 1959)	0.049 (df = 1949)	0.049 (df = 1949)	0.037 (df = 1951)
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: Combined Fixed Effects Models

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	0.001	-0.001	-0.0005
	(0.0005)	(0.001)	(0.001)
Observations	1,971	1,971	1,971
R^2	0.526	0.517	0.177
Adjusted R^2	0.518	0.510	0.163
Residual Std. Error	0.037 (df = 1941)	0.037 (df = 1941)	0.049 (df = 1939)
Note:			*p<0.1; **p<0.05; ***p<0.01

Next, we fail to see any significance for LN_CEI under different combinations of fixed effects (Table 5, Panel B). One reasonable interpretation could be that outside the setting of large-scale climate concerns and disruptions, the market dynamics for pricing carbon risk may be simpler and less interactive. During periods like the COVID-19 pandemic, the effects of heightened market volatility, shifting investor preferences and government interventions may overlap and lead to a more complex environment with different factors interacting more intensely which can amplify their impact on carbon risk pricing as we saw earlier. In comparison, outside of such periods, we can see a more stable market environment. Here, the interactions between these factors may be less intense leading to simpler relationships where traditional systematic risk factors, like default risk, are priced more significantly.

These results highlight how carbon risk pricing varies under stable versus disrupted market conditions and intensified climate concerns. They imply that carbon risk pricing may not be a consistently visible factor in bond markets, rather it is contingent on investor preferences and periods of heightened external pressures or attention. Furthermore, they suggest that the inclusion of the pandemic in our initial analysis could have distorted our conclusions about the general relationship between a firm's CEI and its bonds' future excess returns. COVID-19 amplified carbon risk pricing due to heightened investor concerns about sustainability and climate-related risks. This highlights the importance of temporal events which lead to a mispricing of carbon risk as highlighted by Pástor et al. (2022).

While our findings show that carbon risk remains systematically mispriced at the industry level outside the pandemic, its varying significance under different specifications can point towards its episodic nature. This can imply that multiple factors are influencing its integration into financial markets. Future research should focus on the interaction between these different factors and uncover the conditions that amplify or suppress carbon risk pricing.

C. Testing the Investor Preference Hypothesis

As we saw under the robustness check for COVID-19, while carbon risk can be systematically priced, the degree of its impact can vary over time. Specifically when investors' non-pecuniary preferences for greener assets increase during periods of intensified environmental concerns. During these periods, bonds from low CEI firms can outperform the ones from high CEI firms, not because of the fundamental risk-return relationship but because of increasing investor concerns and preferences for sustainability. Although removing the effects of large-scale disruptions already gave support to this hypothesis, there can be events of a

smaller scale which may also have similar characteristics. We further test this hypothesis to investigate if the pricing of carbon risk is moderated by periods where climate concerns intensify more than average. Under the hypothesis, we expect CEI to have a negative and significant relationship with bond excess returns if climate-related concerns unexpectedly strengthen. We use the innovations in Crimson Hexagon (CH) Negative Climate Change News Index and the Wall Street Journal (WSJ) Climate Change News Index constructed by Engle et al. (2020) as a proxy for change in climate concerns.

We start with the first index. To identify periods of high concern, we construct a dummy variable, HIGH_CHNN, by assigning a value of 1 to those years where the innovation in the CH Negative News Index exceeds the median value of the index and assigning 0 otherwise. To test for moderation, we interact HIGH_CHNN with LN_CEI and reexamine our baseline regressions by including the interaction term (LN_CEI:HIGH_CHNN1). We choose to test this on the baseline regression since adding fixed effects may absorb the interaction term if it is constant within the fixed effects groups. Our results in Table 6, Panel A show that LN_CEI is not directly significant and does not explain bond returns independently. HIGH_CHNN1 on its own is highly significant and positive, indicating that bond excess returns tend to increase during this time. This means that overall, investors display risk aversion and seek higher returns in time when the risk they hold increases, consistent with traditional risk pricing theory. When both of their effects are combined in the interaction term (LN_CEI:HIGH_CHNN1), we see a significant and negative relationship. Bonds of firms with higher CEI earn lower returns during high negative climate change news. In periods of low climate concern (HIGH_CHNN = 0), LN_CEI has no significant impact on bond returns since its main effect is insignificant. In periods of high climate concern (HIGH_CHNN = 1), the main effect of HIGH_CHNN leads to an overall increase in bond excess returns but the negative interaction term means that this increase in returns is diminished for bonds of carbon-intensive firms. This highlights that carbon-intensive firms are penalized, reducing their returns relative to others. The economic effect of the interaction is also slightly higher than what we found in previous regressions (coefficient = -0.006)

This interesting dynamic gives more nuance to our understanding of how climate concerns amplify the market's focus on carbon risk. So even though there may be a general increase in returns to compensate for the increased risk, there may also be increased scrutiny for carbon-intensive firms and investor preferences may shift towards greener assets leading to lower relative returns for carbon intensive

TABLE 6: MODERATION OF CARBON RISK PRIICING BY PERIODS OF HIGH CLIMATE CONCERN

This table presents the regression results analyzing the interaction between carbon emissions intensity (LN_CEI) and periods of heightened climate concerns, as measured by the Crimson Hexagon (CH) Negative Climate Change News Index and the Wall Street Journal (WSJ) Climate Change News Index. LN_CEI represents the carbon emissions intensity of the firms. HIGH_CHNN and HIGH_WSJ are dummy variables identifying years of heightened climate concerns based on the CH and WSJ indexes, respectively, with values of 1 assigned when innovations in these indexes exceed their median values. Interaction terms (LN_CEI:HIGH_CHNN and LN_CEI:HIGH_WSJ) capture the combined effects of carbon intensity and heightened climate concerns. No fixed effects have been applied. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Panel A shows the estimates under CH negative news index and Panel B shows the estimates WSJ index. Standard t-statistics are reported in the parenthesis. *, **, and*** indicate the significance at a 10%, 5% and 1% level, respectively.

Panel A: CH Negative Climate Change News Index

	Dependent variable:
	EXCESS RETURNS
LN_CEI	-0.0002
	(0.001)
HIGH_CHNN1	0.058***
	(0.012)
LN_CEI:HIGH_CHNN1	-0.006**
	(0.003)
Observations	1,037
R^2	0.238
Adjusted R^2	0.228
Residual Std. Error	0.057 (df = 1023)
Note:	*p<0.1; **p<0.05; ***p<0.01

Panel B: WSJ Climate Change News Index

	Dependent variable:
	EXCESS RETURNS
LN_CEI	-0.0003
	(0.001)
HIGH_WSJ1	0.040***
	(0.013)
LN_CEI:HIGH_WSJ1	-0.001
	(0.003)
Observations	483
R^2	0.221
Adjusted R^2	0.200
Residual Std. Error	0.055 (df = 469)
Note:	*p<0.1; **p<0.05; ***p<0.01

firms. This finding gives support to our second hypothesis and connects back to our earlier discussion on context sensitivity of carbon risk pricing.

We follow the same process for creating a dummy variable for the index based on WSJ (Table 6, Panel B). Just like in the previous case, LN_CEI does not show any significance while the main effects of HIGH_WSJ show a positive and significant relationship leading to a similar interpretation as HIGH_CHNN. The interaction term (LN_CEI:HIGH_WSJ1) is, however, insignificant in contrast to our previous results. A major reason could be that WSJ captures all types of media coverage on climate related topics irrespective of their neutral, positive or negative tone. The impact of high carbon intensity on bond returns is not pronounced during periods of increased general media attention as mixed news may dilute the effect of carbon risk on bond returns or investors may not be sensitive to it. The difference in our results can highlight that carbon risk is priced more specifically when negative concerns about climate strengthen which gives a better understanding of the subtle role of investor sentiment in pricing of carbon risk. Moreover, this role of investor sentiment may be more enhanced when using indexes tailored to the Eurozone region as the current indexes were constructed more generally to understand the dynamics of hedging climate change news in the US stock market (Engle et al., 2020).

V. Conclusion

Our paper aims to find some common ground among the mixed evidence within the fast- growing Climate Finance literature that examines whether financial markets can efficiently price climate change-related risks. By investigating whether carbon risk, estimated by a firm's CEI, is priced in the cross-section of the Eurozone corporate bond market, we provide a valuable addition to the previous literature, which mainly focuses on equities (e.g., Bolton and Kacperczyk, 2021) or the U.S. (e.g., Huyhn and Xia, 2020). By using fixed-effect panel regressions, we find overall evidence of a systematic mispricing of carbon risk, rejecting the carbon risk premium hypothesis. This result is consistent with the findings of Duan et al. (2021). We also find evidence for the episodic and context-sensitive nature of carbon risk pricing in corporate bonds. Leveraging the two climate change news indexes constructed by Engle et al. (2020), we further find support for this by testing the investor preference hypothesis which proposes that Eurozone corporate bonds issued by firms with higher CEI perform worse when climate concerns unexpectedly strengthen. We find evidence in line with this proposition when we exclude periods of extreme market disruption which amplify the mispricing of carbon risk similar to the findings of Pástor et al. (2022). The testing of the second hypothesis particularly

gives us insight into how negative sentiments of investors moderate the pricing of carbon risk in the bond market. Our results mainly serve to highlight the context-sensitivity and temporal nature of carbon risk pricing. We also uncover potential long-term trends in carbon risk pricing during periods of relative stability by testing our results with systematic risk factors estimated by a larger rolling window which adds value to our research.

Despite the value of our study, our analysis is subject to several limitations. After filtering for complete cases, the number of annual observations in our dataset is reduced substantially. Moreover, our data is inherently unbalanced, since most bonds in the sample were issued toward the end of the period of interest. This can cause biases since bonds issued later in the sample period might reflect heightened sensitivity to carbon risk as investor awareness and regulations would have evolved in recent years. Furthermore, there is a risk of bias in our estimates because of the limited geographic and sectoral diversity. We try to handle such constraints by controlling for time, industry, and country-fixed effects in our regression models.

Another limitation is our reliance on monthly last prices rather than intraday price and volume data, which might introduce noise and limit the accuracy of our estimated bond returns. Bessembinder et al.'s (2008) trade-weighted price methodology could have enhanced precision if implemented with comprehensive intraday data. Another limitation is that we employed rolling regressions to estimate time-varying factor loadings. A multivariate GARCH-BEKK specification could have offered more precise modeling of time-varying covariances and dynamic interactions. Another limitation is that we use standard test statistics in our regressions, which could affect the robustness of our model's significance.

Our study attempts to serve as an inspiration and catalyst for future research into the evolving role of carbon risk in financial markets. Future research can build further upon our study and address its current limitations. For instance, orthogonalized CEI measures could also improve estimates by isolating pure carbon risk from other confounding factors. Moreover, using intraday bond price and volume data could improve the accuracy of bond return calculations and further validate findings. Better computation of the systematic risk factors would also be an improvement over our current study. Most importantly, it would be valuable if future researchers would study the interplay between market shocks, and industry- and country-specific factors over different dimensions. Our results suggest that carbon risk pricing is highly dynamic, exacerbated during market shocks, and is priced differently over the long run and in periods of relative

stability. For instance, in stable periods, industry-specific factors play a more important role. Given the number of dynamics at play here, we need more nuanced and strong empirical studies examining how these various factors interact and develop over time to better understand when and how carbon risk becomes a dominant factor in bond pricing. Such studies would help offer a clearer framework for incorporating carbon risk into investment strategies and policy making.

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Appendix

Table A1: VARIABLE DEFINITIONS

The following table presents a summary of the definitions and data sources of the variables used in our main regressions.

Variables	Description	Data Sources
Excess Return	It is the future excess return on bond in year t +1. Risk free rate to calculate the excess return of the bond is 1-month EURIBOR. The monthly bond return is estimated by calculating the dirty price of the bond by first adding accrued interest to the end-of-month clean price, then dividing it by previous months dirty price and subtracting one at the end.	Bloomberg, ECB Data Portal, Eurostat
Bond Market Beta (Beta_BMKT)	Estimated from the monthly rolling regressions of individual bond excess returns on the excess bond market return.	Bloomberg, Eurostat, ECB Data Portal
Default Beta (Beta_DEFAULT)	Estimated through a rolling-regression of excess bond returns on the default spread over a 24/36-month window.	Bloomberg
Term Beta (Beta_TERM)	Estimated by regressing excess bond returns on term spread over a 24/36-month window.	Bloomberg
Macroeconomic Uncertainty Beta (Beta_UNC)	Estimated by regressing excess bond returns on changes in Global Economic Uncertainty index over a 24/36-month window.	EPU indexes
Illiquidity beta (Beta_ILLIQ)	Estimated by regressing excess bond returns on the over spread between 1- month EURIBOR and 1- month EONIA rate over a 24/36-month window.	ECB Data Portal
Lagged_Return	It is the past annual excess return on the bond in year t -1.	Bloomberg
VAR	The second lowest monthly return observation over a 24/36-month rolling window multiplied it by −1	Bloomberg
rating_score	Bond rating converted into numerical scores (1-AAA to 22-D)	Moody's
Maturity	Time remaining until bond maturity, measured in years	Bloomberg
Log_amt_outstanding	Natural log of amount outstanding of the bond	Bloomberg
LN_CEI	Log transformation of firm's carbon emissions intensity metric constructed by dividing carbon emissions of the firm by its sales (metric tons/million Euro)	MSCI & Bloomberg

Table A2: THE MIXED EFFECT MODEL

This table reports the average and slope coefficients from panel regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI) with all control variables under different combinations of mixed effects. The dependent variable is the corporate bond excess returns (EXCESS RETURNS) in the year t +1. The key independent variable LN_CEI is based on the firm-level carbon emissions intensity in the previous year t. Scaled betas estimated from 24 month rolling regressions windows are used. All other variables are defined in the Appendix, Table A1. Column (1) represents industry plus dates, column (2) represents country plus dates, and column (3) presents the results for country plus industry mixed effects. Standard t-statistics are reported in the parenthesis. ∗, ∗∗, and∗∗∗ indicate the significance at a 10%, 5% and 1% level, respectively.

Mixed Effects Model With Different Combinations

	Dependent variable:		
	EXCESS RETURNS		
	(1)	(2)	(3)
LN_CEI	-0.001***	0.0002	0.0002
	(0.0004)	(0.0003)	(0.0005)
VAR	0.422***	0.393***	0.400***
	(0.050)	(0.050)	(0.064)
rating_score	0.001**	0.0004**	0.001**
	(0.0002)	(0.0002)	(0.0003)
Maturity	0.0004***	0.001***	0.002***
	(0.0001)	(0.0001)	(0.0002)
log_amt_outstanding	0.001**	0.001	0.001**
	(0.0004)	(0.0004)	(0.001)
Lagged_Return	-0.169***	-0.163***	-0.241***
	(0.013)	(0.013)	(0.012)
Beta_BMKT	0.048	0.048	-0.262**
	(0.101)	(0.101)	(0.131)
Beta_DEFAULT	-0.297***	-0.306***	-1.001***
	(0.062)	(0.063)	(0.082)
Beta_TERM	-0.765***	-0.837***	-2.361***
	(0.137)	(0.138)	(0.175)
Beta_UNC	-0.299*	-0.387**	-1.532***
	(0.171)	(0.173)	(0.221)
Beta_ILLIQ	-0.003	-0.010	0.084***
	(0.022)	(0.022)	(0.029)
Constant	0.019	0.020	-0.027***
	(0.031)	(0.031)	(0.010)
Observations	3,427	3,427	3,427
Log Likelihood	6,581.425	6,603.931	5,572.901
Akaike Inf. Crit.	-13,132.850	-13,177.860	-11,115.800
Bayesian Inf. Crit.	-13,040.760	-13,085.770	-11,023.710
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A3: VARIANCE DEMOPOSITION OF THE INDUSTRY PLUS DATES MIXED EFFECTS MODEL

This table presents the variance components derived from the mixed effects model with industry plus dates mixed effects. It shows the proportion of total variance attributable to industry-level effects, time-level (Dates) effects, and residual variation. The results highlight that bond returns exhibit greater variability over time compared to differences across industries, emphasizing the dominant role of time-related factors such as regulatory changes or macroeconomic events in driving bond returns.

Variance Component	Variance	Proportion of Total Variance Explained
Industry-level variance	0.00000	0.04%
Dates-level variance	0.00904	88.20%
Residual variance	0.00120	11.76%