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THE RISE OF CLIMATE RISKS: EVIDENCE FROM EXPECTED DEFAULT FREQUENCIES FOR FIRMS

by Matilde Faralli* and Francesco Ruggiero**

Abstract

The paper investigates the relationship between climate transition risk and credit risk by analysing firms' carbon emissions and Moody's Expected Default Frequencies (EDFs). The results suggest that the Paris Agreement was a turning point in the relationship between emissions and credit risk: following the Agreement, the correlation between emission levels and EDFs became positive and statistically significant. By decomposing the EDFs into their core components, increased asset volatility is found to be the main channel through which transition risk affects credit risk for high-emissions companies. The analysis sheds light on the mechanisms linking climate transition risk to financial risk. The results are robust across different model specifications, control variables and geographic areas, and indicate that climate-related financial risks have become increasingly important for credit markets.

JEL Classification: G30, G32, C13, H23.

Keywords: Climate Change, Credit Risk, EDF, Carbon Emissions, Transition Risk.

Sintesi

Il lavoro analizza la relazione tra rischio di transizione climatica e rischio di credito esaminando le emissioni di carbonio delle imprese e le Expected Default Frequencies (EDFs) stimate da Moody's. I risultati suggeriscono che l'Accordo di Parigi ha rappresentato un punto di svolta nella relazione tra emissioni e rischio di credito: successivamente a quell'accordo la correlazione statisticamente tra livelli delle emissioni ed EDFs è divenuta positiva e statisticamente significativa. Scomponendo le EDFs nelle loro componenti fondamentali, la maggiore volatilità degli attivi viene identificato come il principale canale attraverso cui il rischio di transizione incide sul rischio di credito per le imprese ad alte emissioni. L'analisi contribuisce a chiarire i meccanismi che collegano il rischio climatico di transizione al rischio finanziario. I risultati si mostrano robusti rispetto a diverse specificazioni del modello, variabili di controllo e aree geografiche, e indicano che i rischi finanziari legati al clima hanno assunto una crescente rilevanza per i mercati del credito.

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CONTENTS

1. Introduction

With increasing attention devoted to climate issues, scholars have studied the effect of climate change on the economy from several perspectives.[1] A fast-growing strand of the literature investigates the relationship between climate-transition risk (i.e. the risks stemming from implementing policy mitigating strategies) and firms' credit risk. Measuring this link is complicated because both variables suffer from endogeneity problems and measurement errors. Using ESG ratings as a proxy for firms' sustainability, earlier studies show that an increase in ESG scores leads to lower CDS spreads (Barth *et al.*, 2022), better credit ratings (Devalle *et al.*, 2017) and lower bond risk premia (Kotró and Márkus, 2020).

Other studies use carbon emissions to investigate the effect of transition risk on bond ratings and yield spreads (Seltzer *et al.*, 2022), option implied volatility slope (Ilhan *et al.*, 2021), CDS spreads (Blasberg *et al.*, 2021) and market-implied distance-to-default (Bouchet and Le Guenedal, 2020; Capasso *et al.*, 2020; Carbone *et al.*, 2021; Kabir *et al.*, 2021). These latter studies construct a measure of default risk by estimating Merton's distance to default (Merton, 1974). Capasso *et al.* (2020) and Kabir *et al.* (2021) find a positive correlation between the probability of default and firms' carbon footprints. Carbone *et al.* (2021) find some evidence only when using relative carbon emissions (i.e. carbon intensity), but not when using emissions in level.

Our paper builds on this latter stream of research. We study the relationship between climate transition risk and credit risk by collecting data on emissions and Moody's Expected Default Frequencies (EDFs) for 1,308 firms from 2008 to 2022. Moody's EDF, a market-implied probability that a firm will default, has a number of desirable features for

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[1]For a summary of the related literature on climate finance, see Giglio *et al.* (2021)

our analysis. First, compared to studies that use computed distances to default, Moody's uses proprietary actual default data to obtain physical probabilities of default.[2] Starting from the risk-neutral distance to default obtained with an improved version of Merton (1974) model, they project the computed distances to default onto actual default data, hence obtaining a linear mapping from the risk-neutral probabilities into physical default probabilities. This approach has the advantage of excluding risk-aversion adjustment components that complicate the inference on the data. Second, using the EDF we study the time dimension of credit risk (i.e. whether climate risks affect the probability of a firm defaulting in 1, 5, or 10 years) as well as the term structure of climate change risk. This provides us with information on when and how transition risks are expected to materialize and how they will affect firms in different sectors. Third, the EDF can be broken down into its main components: asset volatility, the market value of assets, and the default point. This allows us to disentangle the effect of carbon emissions on the different drivers of credit risk and thus indirectly on the default probability. By construction, the EDF drivers fully explain the EDF variability. Hence, by regressing EDF components on emission levels, we can show how carbon emissions individually affect each EDF driver.

In examining how climate-related risks affect credit markets, we distinguish between absolute emissions (measured as total Scope 1 emissions) and relative emissions (measured as carbon intensity), and assess how the market perception of these measures changes over time. Specifically, we regress Moody's 1-, 5-, and 10-year EDFs on absolute direct emissions and emission intensity. Our results indicate that, after accounting for firm fundamentals and sectoral variations, absolute emissions have no effect on credit risk. Instead, we find a positive relationship between carbon intensity and credit risk, consistent with previous

[2] Risk-neutral probabilities are useful tools for pricing derivatives, as they assume market participants are indifferent to risk and only care about expected returns. However, they fail to incorporate real-world risks, such as climate risks, that can significantly impact firms' financial performance. Hence, by taking into account the uncertainty and potential impacts of climate risks, physical probabilities (i.e. historically-based) allow for a more accurate assessment of a firm's credit risk.

studies suggesting that more polluting firms within a sector face higher default risks (Blasberg *et al.*, 2021; Capasso *et al.*, 2020; Carbone *et al.*, 2021; Kabir *et al.*, 2021). However, this relationship is sensitive to specification choices and driven largely by upper-tail observations. We further explore this issue using a quintile regression approach, which confirms that the baseline patterns persist.

We hypothesize that absolute emissions became increasingly relevant for credit risk following the adoption of the Paris Climate Accords (also referred to as the Paris Agreement). To test this, we examine whether the signing and ratification of the agreement marked a structural break in policies, particularly from a corporate perspective. In other words, we explore the relevance of the Paris Agreement as a potential determinant of increased credit risk through its amplifying effect on climate transition risk. Our underlying hypothesis is that for signatory countries guided by the agreement's pledges, the probability of increased transition risk should rise in response to stricter climate regulations, thereby increasing uncertainty for domestic firms.[3] This effect should be more pronounced for firms with higher carbon emissions (top quintiles), which may face greater challenges in complying with stricter carbon regulations. This uncertainty would then directly translate into higher asset volatility, consequently leading to a higher EDF.

In the aftermath of the Paris Agreement, we find that higher direct emissions lead to an increase in the probability of default for firms within the same credit rating class. This finding suggests that policies aimed at reducing carbon emissions are effective in reducing transition risk and improving creditworthiness, highlighting the potential benefits of environmentally responsible practices for firms.

We also provide evidence of the channels through which carbon emissions affect credit risk by breaking-down EDF into its core components: asset volatility, the market value

[3]Although the agreement does not legally bind signatory countries to enforce its pledges, several authors have shown that investors and financial markets react to the signaled increased global commitment on climate action (see Monasterolo and De Angelis, 2020; Kruse *et al.*, 2020; Seltzer *et al.*, 2022).

of assets, and default point. First, we document how each component enters linearly into the EDF. We show how, by construction, higher asset volatility is associated with a higher probability of default, while higher default points and market value of assets reduce default risk. Then, we analyze the effect of carbon emissions on each EDF component. We find that the increased default risk of high emitters is driven by an increase in asset volatility after the Paris Agreement. Finally, we corroborate our hypothesis that firms with high credit risks are penalized only when there are regulations in place that internalize the costs of polluting through an analysis focused on geographical differences. Different countries and regions have varying regulations and policies to address climate change, which can influence the speed and scale of the transition to a low-carbon economy. For instance, the US has been less stringent in implementing carbon reduction policies compared to other countries, while European carbon policies are more stringent and accurately tailored for various sectors. Consistent with our intuition that looser regulation on carbon emissions does not penalize polluting firms, we do not find a clear relationship between emissions and credit risk for US firms. However, when examining the EU sample, we observe that large emitters face a higher credit risk premium compared to their peers. This result is also confirmed when looking at the effect of carbon price surprises connected to the EU Emission Trading System (EU ETS) on credit risk.

To test the robustness of the findings, we conduct a series of supplementary analysis to ensure that our results are not driven by the choice of credit or transition risk proxies. We show that our findings are consistent when using alternative winsorization thresholds, and also different measures of credit risk, including CDS spreads, CDS-implied ratings, and Moody's ratings. In all cases, we observe a positive correlation between credit risk and carbon intensity, but no significant relationship with absolute emissions. We also acknowledge that the EDF, given its sensitivity to market expectations and future credit risk related to the transition to a low-carbon economy, may reflect forward-looking transition risk rather than the long-term, backward-looking impact of carbon emissions, which is typically represented by absolute emissions (Bolton and Kacperczyk, 2021*b*). To address the forward-looking dimension of transition risk, we use Trucost's carbon earnings-at-risk—which captures the potential financial cost firms may incur under future carbon pricing—and the announcement of science-based targets, which are voluntary corporate commitments to reduce greenhouse gas emissions in line with the goals of the Paris Agreement. We perform additional robustness checks to test the consistency of the relationship between carbon emissions and the probability of default. Our results indicate that forward-looking transition risks —measured by carbon earnings-at-risk relative to EBITDA— are positively associated with higher default probabilities. We also find that medium- and long-term EDFs temporarily decline around the announcement of science-based targets for high emitters, suggesting a short-lived reduction in perceived credit risk. Furthermore, the findings remain robust to the inclusion of lagged emission levels, although we observe no significant effect from the short-term rate of change in carbon emissions.

To the best of our knowledge, this is the first paper in the related literature that using Moody's EDFs to proxy the probability of default provides insights into the drivers of climate transition risks on firm-level credit risk before and after the Paris Agreement.[4] This study complements the existing literature in two key aspects. First, we highlight that the signing of the Paris Agreement and the subsequent rise in investors' awareness of climate risks marked a structural break in policies, particularly from a corporate perspective. The Paris Agreement appears to be a significant determinant of increased credit risk through its amplifying effect on climate transition risk. Second, we identify the channels through which carbon emissions affect firms' probability of default, along with the relative weights of each. Our analysis reveals that this influence primarily occurs through increased asset volatility, especially for high-emission firms. Finally, we provide additional evidence that climate regulation strongly

[4]In a different research setting, Acharya *et al.* (2022) use Moody's EDFs to show that heat stress exposure increases credit risk of municipal as well as corporate bonds.

impacts the integration of climate risks into credit risk assessments by offering a comparative analysis of firms in the US and the EU, which are subject to different sets of rules and requirements concerning climate risk.

Related Literature. In the remaining part of this section, we provide a survey of how previous studies dealt with quantifying firms' climate-related risks and their main findings.

Earlier studies addressed this issue using corporate social responsibility metrics (e.g. Stellner *et al.*, 2015) and environmental scores (Höck *et al.*, 2020). For example, Höck *et al.* (2020) show that a higher environmental score leads to lower CDS spreads for firms with ex-ante high creditworthiness, low leverage, and high market capitalization. In contrast, Stellner *et al.* (2015), investigate the effect of higher corporate social responsibility (CSR) scores on credit ratings and zero-volatility spreads (z-spreads); they find that stronger results are driven by countries' ESG performance, suggesting that the regulatory environment allows a larger reduction in credit risk when companies display a higher CSR score.

Other studies used ESG ratings to show how an increase in ESG scores leads to lower CDS spreads (Barth *et al.*, 2022), better ratings by Moody's (Devalle *et al.*, 2017), and lower bonds' risk premia (Kotró and Márkus, 2020). Similarly to Höck *et al.* (2020), also Barth *et al.* (2022) conclude that higher ESG ratings correlate with lower credit risk (proxy by CDS spreads), with a stronger effect for European firms and for firms with medium ESG ratings.[5]

One of the criticisms often raised against the use of ESG data is that they are unstandardized, non-compulsory and not fully transparent in the way they are constructed (see, for example, Berg *et al.*, 2022), thus making it hard to disentangle the drivers of their effect on credit risk.

[5]Another relevant paper belonging to this strand of literature is Henisz and McGlinch (2019). They show that previous years' higher ESG ratings, using RavenPack's reported news, are strongly correlated with lower future assets volatility.

To respond to these criticisms, scholars explored different paths. Seltzer *et al.* (2022) study the effect of poor environmental profiles or high carbon footprints on credit rating scores and bond spreads for firms around the 2015 Paris Agreement. They find that firms with high pre-existing emissions present worse scores and higher spreads, with more pronounced effects in strictly regulated US states. Blasberg *et al.* (2021) study the correlation between CDS spreads and transition risk, proxied by carbon intensity and emissions. They find that climate risk has a heterogeneous effect across sectors and on the term structure of firms' credit risk. Ilhan *et al.* (2021) provide evidence that an increase in carbon intensity leads to a larger option implied volatility slope, in particular for left tail regions.

Our paper relies on previous studies in choosing carbon disclosures as a proxy of climate risk, more precisely transition risk. However, a recent strand of literature relies on the construction of climate-corrected ratings. Kölbel *et al.* (2024) train an AI algorithm for languages to see whether regulatory risk disclosures affect CDS spread. They find that while disclosing transition risks increases CDS spreads, especially after the Paris Climate Agreement of 2015, disclosing physical risks decreases CDS spreads. Other related papers such as Klusak *et al.* (2023) construct a model similar to S&P's such as to incorporate climate physical risks into sovereign ratings for possible future climate scenarios. Sautner *et al.* (2023) use quarterly earnings calls to construct an annual firm-level measure of firms' exposure to climate. Further work might use one of these novel firms' climate exposure variables to corroborate our findings further.

Finally, it is important to note that our paper specifically addresses the risks associated with the potential implementation of mitigation strategies. However, there is an ever-expanding body of literature that delves into the consequences of directly implementing carbon taxes on firms' default risks. For instance, Di Virgilio *et al.* (2023) conducted a study investigating the impact of different levels of carbon taxes on energy prices and revealed that the probability of default for 200,000 non-financial Italian firms was only minimally affected. Similarly, Aiello and Angelico (2023) observed that the imposition of a carbon tax had a modest impact on default rates for Italian banks, which remained below historical averages. These findings align with the growing consensus, prompting several central banks to undertake stress tests to comprehensively evaluate the quantifiable impact of climate risks on financial institutions.

Our paper is structured as follows. Section 2 presents the data and methodology. Section 3 provides descriptive evidence of the relationship between carbon emissions and the probability of default. Section 4 discusses the empirical findings, and Section 5 reports the results of a battery of robustness checks. Finally, Section 6 concludes the paper.

2. Data and Methodology

2.1. Data

The dataset is constructed by gathering data from four main databases: carbon emissions are retrieved from MSCI, EDFs and ratings from Moody's CreditEdge, CDS spreads and stock prices are obtained from Refinitiv, and balance sheet information is sourced from CRSP and Compustat. We also collect carbon-earnings-at-risk data from Trucost to enhance our analysis with a forward-looking measure of transition risk..

Our initial sample comprises all firms with yearly carbon emissions listed in the MSCI database for three advanced economies: the United States, United Kingdom, and the European Union, covering the period from 2008 to the end of 2022. We match the data with Moody's CreditEdge to obtain monthly Expected Default Frequencies (EDFs), EDF components (asset volatility, market value of assets and default point) and Moody's credit ratings. Additionally, we incorporate quarterly balance sheet data from Compustat Global and North America via WRDS.[6]

We also collect 5-year single-name CDS spreads for unsecured debt with the "Modified Modified Restructuring" clause (MM14) from 2008 to 2023. All CDS spreads are in US

[6] When possible we impute missing values using previous quarter values.

dollars. Following Gao *et al.* (2021) the data are aggregated at the monthly level by taking the mean over the month within each entity. We exclude all CDSs with a spread higher than 4000 basis points (Zhang *et al.*, 2009) and illiquid CDS (Blasberg *et al.*, 2021).[7]

As part of our strategy to identify the effect of climate on firms' credit risk, we apply several filters to the sample analyzed. We winsorize EDF, EDF components, CDS Spread, absolute emission and emission intensity at the 5% level to avoid results driven by a few distressed companies, extremely high carbon emitters, or incorrectly reporting zero emissions. We then discard firms with less than 7 years of complete data. Finally, we exclude firms in the financial sector, public administration and other services sectors to avoid misinterpretation of the outcomes driven by these entities' significantly different financial behavior.

The final dataset includes 1,308 firms from 2008 to 2022, containing monthly EDFs, quarterly balance sheet information, and yearly carbon emissions. For the analysis, we additionally use two sub-samples: one consisting of 205 firms with monthly CDS spreads, allowing comparisons with previous studies, and another comprising 615 firms with Moody's ratings to control for credit risk.

2.2. Methodology

To study how transition risks influence firms' credit risks, our primary outcome variables are Expected Default Frequency (EDF) over 1-year, 5-year, and 10-year horizons. EDF represents the likelihood of a firm's default within a specified period. Our independent variables of interest are absolute emissions and emissions intensity as proxies for transition risks. Absolute emissions reflect alignment with zero-carbon emissions goals outlined by carbon policies (Bolton and Kacperczyk, 2021*a*), while emissions intensity is included to address potential reliance on intensity measures in market valuation as well to ensure comparability across firms (Hartzmark and Shue, 2022; Zhang, 2025).

[7]The results are consistent when using median and end-of-the-month CDS spreads.

We estimate the baseline regression model using a high-dimensional fixed effects methodology, specified as follows:

$$EDF_{i,t} = \alpha + \beta_1 * Emissions_{i,t} + \delta X_{i,t-1} + FE + \epsilon_{i,t} \tag{1}$$

where EDF is the dependent variable measured at monthly frequency, and the key independent variables are yearly emissions—measured as $Log(Scope1)$ and *Carbon Intensity*. The vector $X_{i,t-1}$ contains control variables at in the previous quarter, specifically firm size (logarithm of total assets), debt ratio, operating margin ratio, and capital intensity. Additionally, we include quarterly intangible capital to control for firm-level innovation and efficiency. Given that default probability is influenced by several firm-specific factors, these control variables help isolate the effect of the climate variable on each firm's default probability.

To address the potential concern that contemporaneous absolute emissions might primarily reflect a firm's sales activity (Zhang, 2025), we also include current log sales as a control variable. Since emissions data are recorded annually, we use yearly sales data for consistency. Other control variables, however, are measured quarterly and lagged by one quarter.[8]

Lastly, we include a fixed effects (FE) matrix at the country, sector, and calendar-year levels. Country-fixed effects control for variations in economic, regulatory, and institutional factors across different nations, while sector-fixed effects account for sector-specific dynamics, such as varying levels of carbon intensity or default risk inherent to certain industries. Year-fixed effects capture significant events, such as the 2007–2008 financial crisis or the COVID-19 pandemic, both of which globally increased default probabilities. To account for within-firm correlation, which arises because EDF is measured monthly while emissions are reported yearly, we follow standard practice in the literature and cluster standard errors at the firm

[8]Another concern is that emissions are released with a 10-12 months lag (Zhang, 2025). For robustness, table B10 replicates the baseline analysis with lagged variables.

level.

3. Descriptive Statistics

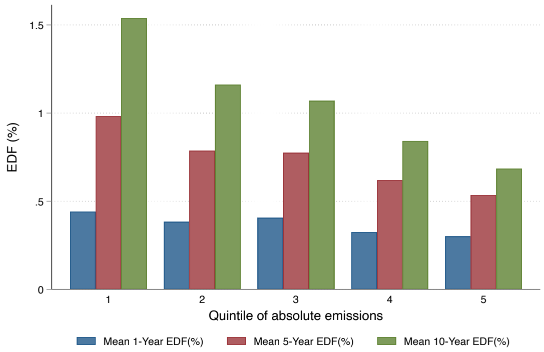
The final dataset encompasses 1308 firms, offering a broad coverage across geographical regions and sectors. Geographically, the sample includes 58% of firms from the United States, 30% from the Euro Area, and 12% from the United Kingdom. Sector-wise, around 46% of the companies are from the manufacturing sector, followed by 9% in the information sector, with the fewest firms in agriculture, management, and education sectors.

Table 1. Summary Statistics

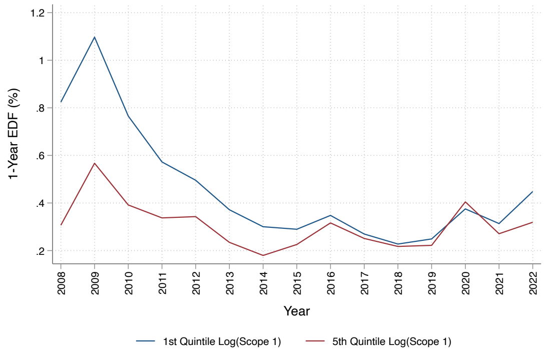
Variables	Mean	Median	SD	Min	Max	Observation
1 Year EDF (%)	0.37	0.09	0.61	0.01	2.34	213,555
5 Year EDF (%)	0.73	0.43	0.75	0.10	2.89	213,555
10 Year EDF (%)	1.04	0.80	0.79	0.20	3.12	213,555
Asset Volatility	21.83	20.29	8.50	9.90	40.89	213,555
Log(Market Value Assets)	8.59	8.47	1.47	6.12	11.40	213,555
Log(Default Point)	7.09	7.07	1.71	3.94	10.14	213,555
Mean CDS Spreads	112.98	77.51	96.17	27.25	394.43	34,159
Moody's Ratings	10.10	9.00	3.36	1.00	21.00	82,848
Derived CDS Ratings	8.11	8.00	3.79	1.00	21.00	43,205
Log(Scope 1)	10.49	10.25	2.81	5.42	15.94	17,909
Carbon Intensity	1.00	0.11	2.17	0.00	8.56	17,909
Log(Current Sales)	7.87	7.82	1.67	0.00	13.32	17,909
Size	8.13	8.01	1.67	1.74	13.65	71,246
Debt Ratio	0.27	0.26	0.21	0.00	4.28	71,246
Operating Margin Ratio	-0.49	0.15	28.28	-4189.50	36.05	71,246
Capital Intensity	0.26	0.19	0.22	0.00	1.00	71,246
Intangible Assets	0.23	0.18	0.20	0.00	1.26	71,246

Note: 1-Year EDF, 5-Year EDF, 10-Year EDF, 5-Year CDS Spreads, Log(Scope 1) and Carbon Intensity are winsorized at the bottom and top 5%. The number of observations varies depending on the data frequency: EDF and EDF components (asset volatility, market value of assets, and default point), CDS spreads, and ratings are monthly variables. Log(Scope 1), Carbon Intensity and Log(Current Sales) are reported at the firm-year level (17,909 observations), and fundamentals are reported at the firm-quarter level (71,246 observations). See Table B1 for variables' description and sources.

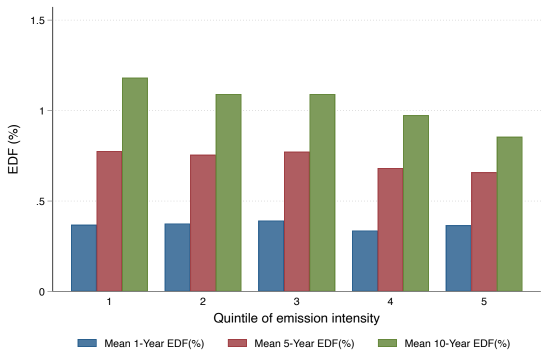
Figure 1. EDF Trends by Absolute Emissions and Emission Intensity: Quintile and Time Series Comparisons



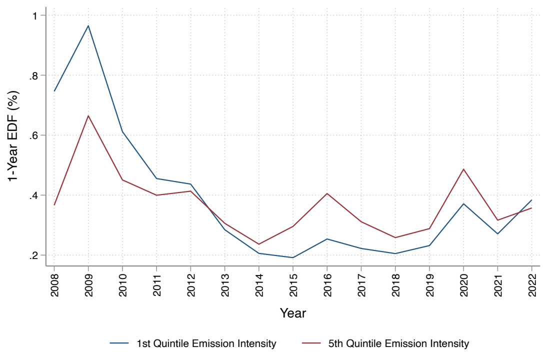
(a) EDF by absolute emission



(b) 1-Year EDF by quintiles of absolute emission



(c) EDF by emission intensity



(d) 1-Year EDF by quintiles of emission intensity

The figures present the average 1-Year EDF, 5-Year EDF, and 10-Year EDF by quintiles of absolute emissions (a) and emission intensity (c), as well as the time series of the 1-Year EDF for the lowest and highest quintiles of absolute emissions (b) and emission intensity (d). Emissions are measured as the logarithm of Scope 1 emissions, and emission intensity is defined as Scope 1 emissions divided by sales. Quintiles of emissions are estimated within each year. Higher quintiles of emissions represent larger emitters. The EDF and emissions are winsorized at the top and bottom 5%.

Table 1 reports the summary statistics for the main variables in our analysis (see Table B1 for an in-depth description of the variables used in the analysis). The average firm in our sample has a 1-year probability of default of 0.37% and a debt ratio of 27%. As anticipated, we observe a positive term structure of the EDF, where 10-year EDF has a higher mean and lower standard deviation (1% and 0.79%) compared to the 5-year EDF (0.73% and 0.75%) and the 1-year EDF (0.37% and 0.61%).

To explore how emissions relate to credit risk, Figures 1 (a) and (c) show the average 1-year, 5-year, and 10-year EDFs divided by quintiles of total direct emissions and emission intensity, respectively. Figures 1 (b) and (d) display the time series of the 1-year EDF from 2008 to 2022 for the first and fifth quintiles.

In panel (a), we observe that firms in the upper quintiles (high emitters) tend to have a lower probability of default than firms in the first quintile. This result is striking, as it challenges the common expectation that the market penalizes firms with higher carbon footprints. While a size effect could contribute to this descriptive evidence, the fact that this effect persists over longer horizons, even when using carbon intensity in panel (c) —where emissions are scaled by sales, inherently accounting for firm size— adds robustness to this finding.

Turning to the time series, panel (b) reveals that the average 1-year EDF for firms in the top (bottom) quintile significantly increased (decreased) after 2015. This aligns with previous studies highlighting the substantial impact of the 2015 Paris Agreement on shaping investors' and policymakers' perceptions of firms' risks (Bolton and Kacperczyk, 2021*b*; Carbone *et al.*, 2021; Capasso *et al.*, 2020; Seltzer *et al.*, 2022; Barth *et al.*, 2022; Kölbel *et al.*, 2024). A two-sample t-test confirms that the average 1-year EDF for firms in the bottom quintile is not statistically different from those in the top quintile between 2015 and 2021. However, the difference becomes statistically significant again in 2022.

Panel (d) shows that for emission intensity, the EDFs of the first and fifth quintiles become statistically indistinguishable as early as 2011. However, firms in the top quintile exhibit significantly higher risk in 2015, 2016, 2017, and 2020. The appendix (Figure A1) provides a detailed view of all quintiles for both total direct emissions and emission intensity, confirming similar trends over longer horizons.

4. Results

4.1. Carbon Intensity and Credit Risk

We begin by examining the relationship between carbon emissions and expected default frequencies (EDFs) at 1-year, 5-year, and 10-year horizons. Our main variables of interest are log(Scope 1) emissions and carbon intensity. Log(Scope 1) measures direct carbon emissions from sources owned or controlled by the firm, while carbon intensity, calculated as Scope 1 carbon emissions over total sales, reflects a firm's efficiency in managing carbon output relative to its economic activity.

Table 2 summarizes the baseline relationship between emissions metrics and EDFs. In detail, Columns (1) and (2) of Table 2 suggest a negative correlation between both absolute emissions and emission intensity with default probability across all horizons. For every 1% increase in absolute emissions, the 1-year EDF decreases by 0.0180 percentage points, while the 5-year and 10-year EDFs decrease by 0.0550 and 0.103 percentage points, respectively. Similarly, higher carbon intensity is associated with lower default probability in the medium (5-year) and long term (10-year), by 0.23 and 0.049 percentage points respectively.

However, once firm-level controls and sector fixed effects are introduced in columns (3) and (4) to account for firm fundamentals and within-sector variation, the results change notably. In the full specification, the effect of absolute emissions becomes statistically insignificant, while carbon intensity shows a positive and significant relationship with credit risk. Specifically, a 1% increase in carbon intensity corresponds to increases of 0.016, 0.023,

Table 2. Analysis using Emission Levels and Intensity

Panel A:	1-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.018***		0.008	
	(0.004)		(0.007)	
Carbon Intensity		-0.005		0.016**
		(0.005)		(0.007)
R^2	0.11	0.10	0.19	0.19
Panel B:	**5-Year EDF**			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.055***		0.014	
	(0.005)		(0.009)	
Carbon Intensity		-0.023***		0.023**
		(0.008)		(0.009)
R^2	0.08	0.04	0.22	0.22
Panel C:	**10-Year EDF**			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.103***		0.004	
	(0.006)		(0.009)	
Carbon Intensity		-0.049***		0.019**
		(0.008)		(0.009)
R^2	0.15	0.04	0.34	0.34
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Industry FE	N	N	Y	Y
Controls	N	N	Y	Y
Obs	213,555	213,555	213,555	213,555

Note: The table reports the regression of current log absolute emission and carbon intensity on EDF. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. EDF and emissions are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level. Statistical significance is reported as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

and 0.019 percentage points in the 1-year, 5-year, and 10-year EDF, respectively.[9] [10]

Taken together, these findings suggest that relative emissions, rather than absolute levels, may have informational value in explaining credit risk—but this result is highly sensitive to the treatment of extreme values. In particular, the apparent positive relationship between carbon intensity and EDFs is not robust to alternative winsorization choices, raising caution about interpreting it as evidence of a systematic link. To further investigate heterogeneity in results, we perform a quantile regression analysis, as detailed in Table B3 in the appendix. Columns (1) and (2) —without controls and fixed effects—show a negative correlation between emissions and EDFs. Once controls are included, the relationship turns positive. Figure A2 plots the coefficients across EDF quantiles (5th to 95th percentile) and shows that the positive association becomes statistically significant only above the 60th percentile—i.e., for firms with higher transition risk. This effect is more pronounced for emission intensity, while the impact of total emissions remains generally weak and statistically insignificant across the distribution. These results suggest that transition risk, as proxied by carbon intensity, may matter more for firms with higher credit risk. Although a positive relationship is frequently documented in the literature, we find that it holds predominantly for firms at the extreme end of the emission intensity distribution, questioning the robustness of this finding across the full sample.

Several factors could explain the observed non-significant or even negative relationship between emissions and EDFs. First, high-emission firms often operate in carbon-intensive industries with substantial entry barriers, economies of scale, and market power, potentially

[9] All variables are winsorized at the 5th and 95th percentiles in the baseline specification. Table B2 reports results without winsorization. We observe that when sector and control variables are included, the positive effect of carbon intensity disappears in the non-winsorized version suggesting that coefficients estimated in Table 2 are largely driven by a small number of extreme observations in the upper tail of the carbon intensity distribution.

[10] To address concerns that the observed results may be overstated due to the differing temporal dimensions of EDF and Emissions, Table B13 presents the baseline estimates using EDF aggregated at the yearly level. The results remain consistent under this alternative specification.

reducing competitive pressure and default risk. Second, these firms might be more aware of climate risks and take proactive mitigation measures, such as investing in low-carbon technologies or diversifying activities. Third, the results in the full sample might be driven, at least partially, by the presence of firms subject to different climate-related regulations, which could affect the degree of integration of climate risks into credit risk for those firms. Fourth, firms might benefit from implicit or explicit government subsidies or consumer tolerance for carbon emissions, enhancing their cash flows and reducing default risk. We extend our analysis to account for some of these explanations in detail later in the paper.

In the following section, we validate our findings using alternative measures of creditworthiness, including Mean CDS Spreads, Moody's Ratings, and CDS implicit ratings.

4.2. Other Measures of Credit Risk

To ensure comparability with previous studies, we replicate our initial analysis using alternative measures of credit risk. We begin by examining the correlations between our primary measure, the Expected Default Frequency (EDF), and other commonly used credit risk variables. Table 3 presents the pairwise correlations among 1-year, 5-year, and 10-year EDF; Mean CDS Spreads; Moody's Ratings; and CDS Implied Ratings. All correlation coefficients are statistically significant at the 1% level. Notably, CDS Spreads exhibit strong correlations with all other credit risk measures. Moody's Ratings and CDS Implied Ratings show particularly high correlations with the 10-year EDF (0.68 and 0.77, respectively), although their correlations with the 1-year EDF are notably lower (0.51 for both).

Table 4 replicates our initial baseline specification with year, country, and sector fixed effects, using alternative measures of credit risk. These measures include CDS spreads and ratings from Moody's and CDS-implied sources, where lower values of the rating variable indicate better creditworthiness. It is important to highlight that this analysis is based on a smaller sample size, comprising 205 firms with CDS spreads, 615 firms with Moody's ratings, and 343 firms with CDS-implied ratings.

Table 3. Pairwise correlation of credit risk variables

Variables	(1) CDS Spreads	(2) Moody's Ratings	(3) CDS Implied Ratings	(4) Y1-EDF	(5) Y5-EDF	(6) Y10-EDF
(1) CDS Spreads	1					
(2) Moody's Ratings	0.68***	1				
(3) CDS Implied Ratings	0.77***	0.74***	1			
(4) Y1-EDF	0.65***	0.51***	0.51***	1		
(5) Y5-EDF	0.68***	0.62***	0.60***	0.90***	1	
(6) Y10-EDF	0.65***	0.66***	0.62***	0.75***	0.94***	1

Note: The table reports the pairwise correlation across 1, 5 and 10-year EDF, Mean CDS Spreads, Moody's Ratings and CDS Implied Ratings. Statistical significance are reported such as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table 4 shows that while absolute emissions exhibit no significant relationship with CDS spreads or Moody's ratings (though they correlate with CDS-implied ratings), carbon intensity remains positively associated with all credit risk measures. This pattern suggests that credit markets place greater emphasis on firms' emission efficiency relative to their economic output than on their absolute emission levels.

Table 4. Other measures of credit risk

	Mean CDS		Moody's Ratings		CDS implied Ratings	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	3.913		0.074		0.232**	
	(3.325)		(0.067)		(0.113)	
Carbon Intensity		8.840***		0.140***		0.288***
		(2.909)		(0.051)		(0.077)
Year, Country & Industry FE	Y	Y	Y	Y	Y	Y
Obs	34,159	34,159	82,848	82,848	43,205	43,205
R^2	0.35	0.37	0.49	0.49	0.32	0.34

Note: The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The Mean CDS, Log(Scope 1) and Carbon Intensity are winsorized at the bottom and top 5%. The sample spans the years from 2008 to 2022, including 205 firms with CDS spreads, 615 firms with Moody's ratings, and 343 firms with CDS-implied ratings. Standard errors in parentheses are clustered at the firm level. Statistical significance are reported such as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Interestingly, the positive relationship with credit risk only appears when emissions are considered in relation to economic activity (carbon intensity) rather than in absolute terms, similar to Carbone *et al.* (2021) and Blasberg *et al.* (2021). This observation supports our earlier findings, but also highlights a potential issue with market incentives. The main goal should be to reduce absolute emissions, not just improve relative efficiency.

To investigate whether the Paris Agreement influenced this paradigm by prioritizing absolute emission reduction for both governments and companies, the following section examines how the relationship between emissions and expected default frequency evolves annually throughout our sample period.

4.3. Time Dynamics of Transition and Credit Risk

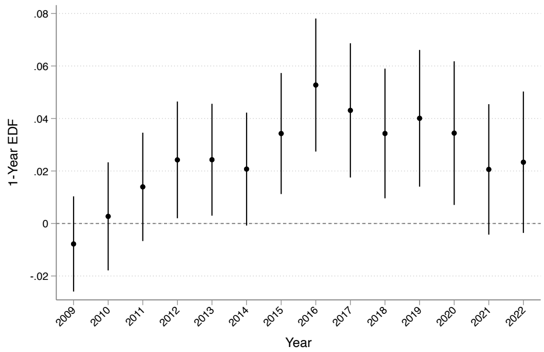
The 2015 Paris Agreement marks a significant turning point in collective awareness of climate risks. We investigate whether the effect of emissions on credit risk changes around this period, motivated by Figures 1 (b) and (d), which show a structural change in 1-year EDFs between top and bottom emission quintiles after 2015. Following the methodology of Acharya *et al.* (2022), we estimate:

$$\text{EDF}_{i,t} = \gamma_i + \gamma_t + \sum_{y=2009}^{2022} I_y[\beta_y Emission_{i,t} + \theta_y Rating_{i,t}] + \beta Emission_{i,t} + \theta Rating_{i,t} + \theta X_{i,t} + \epsilon_{it} \quad (2)$$

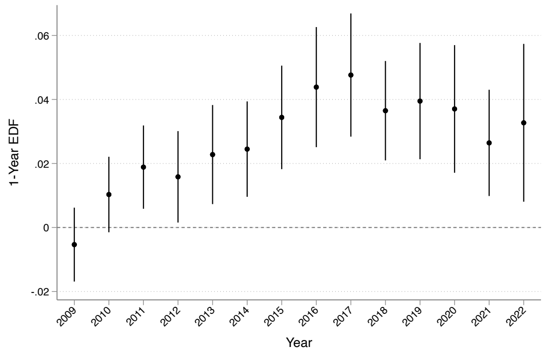
The dependent variables are the 1-year, 5-year, and 10-year EDFs for firm i at time t. The coefficients of interest, β_y, capture the year-by-year sensitivity of EDF to *Emissions*—both absolute and relative (intensity)— compared to the base year 2008. We control for credit quality by including Moody's ratings interacted with year indicators and add firm characteristics, including size, debt ratio, operating margin ratio, capital intensity, intangible assets, and log current-sales. The specification includes firm and year fixed effects, with standard errors clustered at the firm level.

Figure 2 shows the interaction coefficients between log(Scope 1) emissions, carbon intensity, and time (using 2008 as the baseline year), along with their 95% confidence intervals. For all EDF horizons, the coefficients are generally insignificant before 2015, with the exception of the 1-year EDF and emission intensity (Figure b), which displays a positive trend

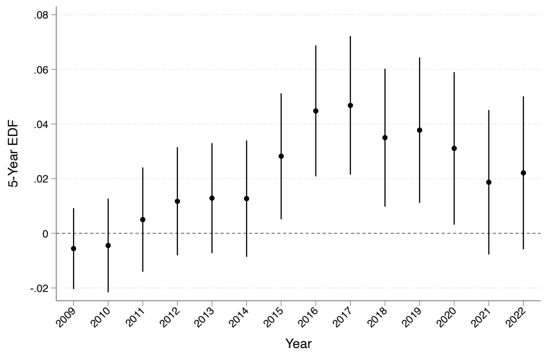
Figure 2. EDF change around the Paris Agreement



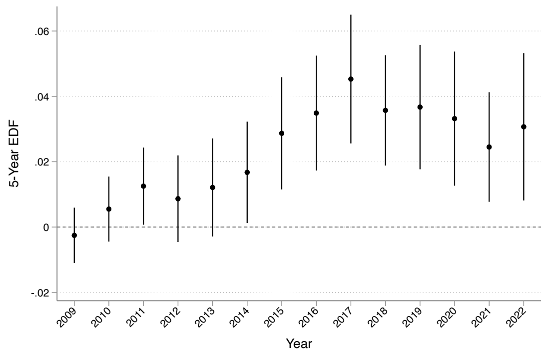
(a) 1-Year EDF & Absolute Emission



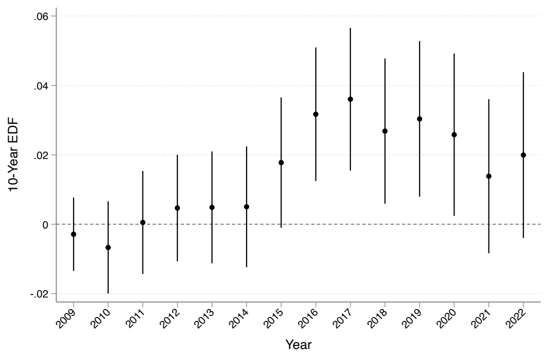
(b) 1-Year EDF & Carbon Intensity



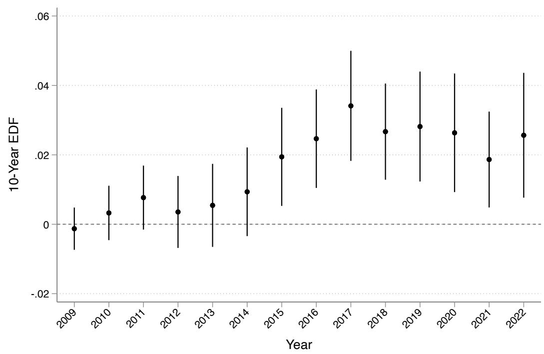
(c) 5-Year EDF & Absolute Emission



(d) 5-Year EDF & Carbon Intensity



(e) 10-Year EDF & Absolute Emission



(f) 10-Year EDF & Carbon Intensity

Note: the figure presents yearly interaction coefficients of absolute emissions (left column) and carbon intensity (right column) with 1-year, 5-year, and 10-year EDFs. The base year is 2008. Coefficients are estimated using firm and year-fixed effects, with 95% confidence intervals displayed.

beginning in 2011. However, we observe a marked shift after 2015, with coefficients becoming strongly positive and significant across all horizons before declining in the last three years of the sample.[11]

The evidence suggests that economic actors internalized implicit climate risk costs following the Paris Agreement, either through direct emission reduction commitments or higher pollution costs imposed by signatory countries. Tables B4 and B5 in the Appendix show the coefficients for absolute emissions and emission intensity increase substantially in magnitude and significance after 2015, nearly doubling in 2016 across all EDF horizons. Although these effects remain significant in subsequent years, they gradually decrease, possibly reflecting uncertainty about the agreement's implementation.

We propose two possible non-mutually exclusive interpretations of these findings. First, the Paris Agreement signaled heightened expectations of future carbon regulation and taxation, potentially increasing costs and reducing revenues for high-emission firms, thereby raising their default risk. Second, the Agreement may have shifted stakeholder preferences, reducing demand for high-emission firms while boosting support for low-carbon alternatives, creating a divergence in default risk profiles.

To further investigate the relationship between carbon emissions and credit risk, the next section decomposes the Expected Default Frequency (EDF) into its key structural components and examines the impact of emissions on each. This component-level analysis enables us to identify the channels through which carbon emissions influence firms' credit risk, thereby shedding light on the underlying drivers of the observed aggregate effect.

[11] Since the regression includes Moody's ratings to control for credit risk across firms, the sample size is smaller than that used in section 4.1, as only 615 firms have ratings. Figures A3 (which do not include ratings) reveal an even larger effect, showing that higher emitters exhibit greater credit risk compared to lower emitters as early as 2011, relative to 2008. This difference continues to grow until 2015, after which it stabilizes.

4.4. Mechanisms: EDF Components

The EDF measures the probability of a firm defaulting over a certain time horizon. It is computed as the probability that the value of the firm falls below a certain threshold (its liabilities payable, also defined as the default point) within a certain time, using an extended version of the Merton (1974) model. Standard EDFs incorporate balance sheet data and market data, thus they tend to express a "market based" default frequency over a given horizon. Three primary components determine a firm's EDF: asset volatility, market value of assets, and the default point. The model employs an iterative approach to simultaneously estimate the value of the assets and their volatility. Once these are determined, the distance to default (DTD) is calculated as the number of standard deviations separating the current value of the assets from the default point; the default point is an estimate of the level of the market value of a company's assets below which the firm would fail to make scheduled debt payments. Finally, the DTD is converted into a PD using a cumulative normal distribution and then calibrated using Moody's historical default data to obtain the EDF.

To understand how transition risks influence EDF, we begin by examining how each EDF component contributes to the overall default probability. Using a series of OLS regressions, we assess the role of these components in explaining variations in EDF. While this approach simplifies the complex relationships underlying EDF dynamics, it provides valuable insights into the channels through which carbon emissions may affect credit risk. The resulting coefficients can be interpreted as the relative weights of each component in explaining EDF variability.

Table 5 presents the estimated coefficients from a series of regressions analyzing the individual effects of each EDF component. Columns (1) to (3) include each component separately, revealing that all coefficients are highly significant. Asset volatility exhibits a strong positive association with EDF. Conversely, higher market values of assets and default points are associated with lower EDF. While the sign of the market value of assets aligns with theoretical expectations—since larger asset values act as a buffer against financial

Table 5. The weights of EDF's Components

	1-Year EDF			1-Year EDF	5-Year EDF	10-Year EDF
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Volatility	0.015***			0.044***	0.062***	0.067***
	(0.001)			(0.002)	(0.002)	(0.002)
Log(Market Value)		-0.111***		-0.628***	-0.864***	-0.836***
		(0.007)		(0.022)	(0.026)	(0.022)
Log(Default Point)			-0.016***	0.612***	0.787***	0.688***
			(0.006)	(0.022)	(0.026)	(0.022)
Constant	0.032	1.320***	0.479***	0.465***	1.213***	1.878***
	(0.030)	(0.062)	(0.043)	(0.066)	(0.086)	(0.093)
Obs	213,555	213,555	213,555	213,555	213,555	213,555
R^2	0.15	0.19	0.12	0.50	0.60	0.66

Note: The dependent variable is the 1-Year EDF in columns 1 to 4, the 5-Year EDF in column 5, and the 10-Year EDF in column 6. All variables are winsorized at the top and bottom 5%. The regressions do not include fixed effects or additional controls. Standard errors in parentheses are clustered at the firm level and statistical significance is reported as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

distress—the negative coefficient on the default point is more difficult to interpret. A higher default point should, in principle, imply a higher likelihood of default, and thus the negative coefficient in column (3) may reflect omitted variable bias due to the exclusion of asset volatility and market value.

We therefore focus on columns (4) to (6), where all EDF components are included jointly. Across all specifications, asset volatility is positively and significantly associated with EDF, with coefficient magnitudes increasing with the time horizon. For example, the coefficient on asset volatility rises from 0.044 in column (4) for the 1-Year EDF to 0.067 in column (6) for the 10-Year EDF. The market value of assets remains negatively and significantly associated with EDF, capturing the role of firm size and financial strength in reducing default probability. The magnitude of this effect is relatively stable across maturities. The default point, which proxies for a firm's debt obligations or leverage, displays a horizon-dependent relationship with EDF. In the 1-Year EDF specification (column 4), the coefficient is 0.612, while for longer horizons (columns 5 and 6), the coefficient increases substantially, indicating that as the default point rises, so does the likelihood of default—consistent with theoretical expectations.

Table 6. Pre and Post Paris Agreement for EDF Component

	Asset Volatility		Log(Market Value of Assets)		Log(Default Point)	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	-0.577***		-0.040***		0.010*	
	(0.076)		(0.008)		(0.005)	
PA*Log(Scope 1)	0.100***		-0.010***		0.010***	
	(0.038)		(0.004)		(0.003)	
Carbon Intensity		-0.163**		-0.013**		0.006
		(0.065)		(0.006)		(0.004)
PA*Carbon Intensity		0.051		-0.013***		0.009***
		(0.044)		(0.004)		(0.003)
Year, Country and Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	213,555	213,555	213,555	213,555	213,555	213,555
R^2	0.65	0.64	0.88	0.88	0.95	0.95

Note: the dependent variables are Asset Volatility, Market Value of Assets, and Default point. The table reports coefficients for Log(Scope 1) and Carbon Intensity, and their interaction with the Paris Agreement (PA) indicator (i.e. taking value 1 after 2015). Emissions and EDF components are winsorized at the top and bottom 5%. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The fixed effects (FE) included are Year, Country and Sector FE. Standard errors in parentheses are clustered at the firm level. Statistical significance is reported as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

We then use the EDF components to identify the channels through which carbon emissions affect EDF. Table 6 presents regression estimates where each EDF component is regressed on carbon emissions and carbon intensity variables, with interactions for the Paris Agreement (PA) indicator to capture potential structural shifts post-PA (i.e. this indicator takes value one after 2015).

The results show that before 2015 higher emissions correlate with lower asset volatility. Following the Paris Agreement, high emitting firms experience a significant increase in asset volatility. This shift likely reflects heightened uncertainty and market repricing of carbon-intensive firms due to the anticipated regulatory, market, and operational adjustments needed to align with climate targets.

For the other two EDF components —market asset value and default point- the results indicate that higher emissions are associated with lower asset values and higher default points. These effects are amplified post-Paris Agreement, where high emitters experience relatively lower asset values and even higher default points compared to before 2015. The effect on firm value is consistent with theoretical expectations, particularly under scenarios where carbon-intensive firms face an increased risk of stranded assets (Bolton *et al.*, 2020).

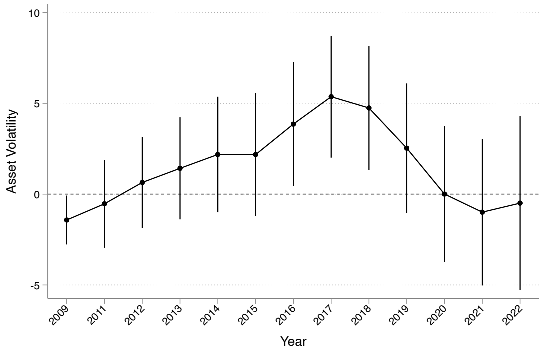
To quantify these effects, we compute the marginal contribution of emissions to EDF through each component. The results suggest that asset volatility is the most influential channel. For a one-standard-deviation increase in asset volatility, the associated rise in EDF attributable to emissions is 0.0374 percentage points. By comparison, the corresponding marginal effects through market value and the default point are 0.0092 and 0.0105 percentage points, respectively.[12]

A similar pattern holds when carbon intensity is used instead of absolute emissions. However, the relationship between carbon intensity and EDF components—particularly asset volatility—appears weaker in the post-2015 period. This is consistent with the interpretation that the Paris Agreement shifted investor and regulatory attention toward firms' absolute emissions rather than their emissions efficiency.

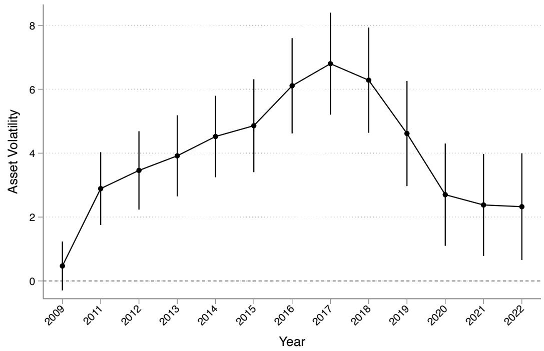
To gain a deeper understanding of the drivers behind the increased EDF for high emitters, we replicate the specification from Acharya *et al.* (2022) to control for variations in firm credit risk and track the evolution of this effect over time. In this context, we plot the difference

[12]These effects are calculated as the product of the estimated coefficient capturing the impact of emissions on each structural component of the EDF —namely, asset volatility, market value, and the default point— and the corresponding coefficient of each component on the EDF. The resulting values represent the marginal contribution of emissions to EDF through each channel, evaluated at a one-standard-deviation increase in the respective component.

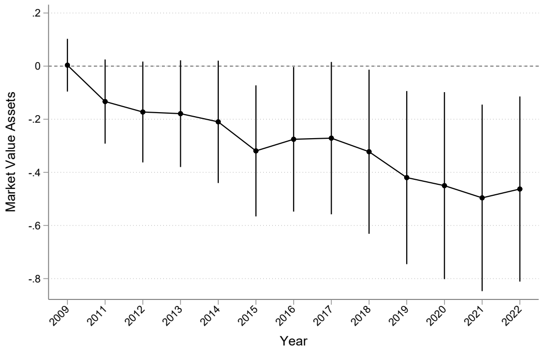
Figure 3. Difference in EDF Components Between Top and Bottom Emission Quintiles



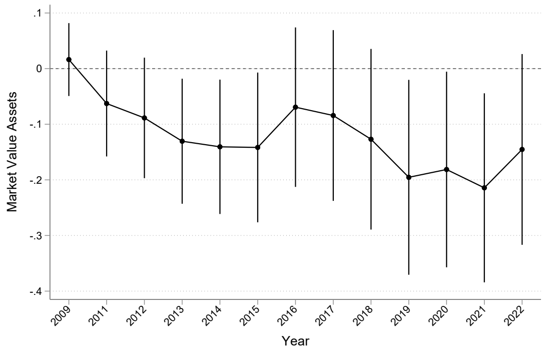
(a) Asset Volatility & Absolute Emission



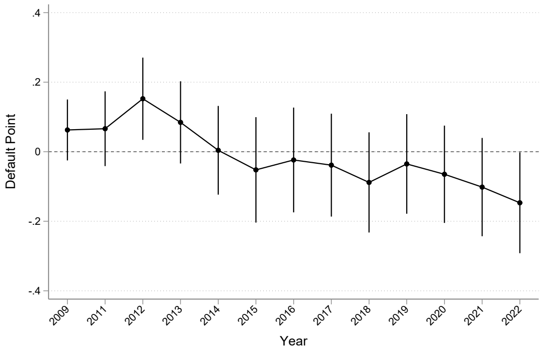
(b) Asset Volatility & Carbon Intensity



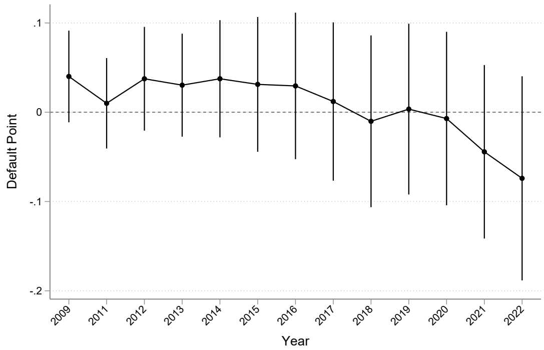
(c) Log(Market Value Assets) & Absolute Emission



(d) Log(Market Value Assets) & Carbon Intensity



(e) Log(Default Point) & Absolute Emission



(f) Log(Default Point) & Carbon Intensity

Note: the figure presents differences in EDF components (asset volatility, market value of assets, and default point) between firms in the top and bottom quintiles of emissions. Panels compare absolute emissions (left column) and carbon intensity (right column), with estimates including country, sector and year-fixed effects. The 95% confidence intervals are also displayed.

between the top quintile and the bottom quintile of emissions, both for absolute emissions and intensity.

$$\text{EDF Component}_{i,t} = \gamma_i + \gamma_t + \sum_{y=2009}^{2022} I_y \left[\beta_y 1(\text{Top Quintile Emission})_{i,t} + \theta_y \text{Rating}_{i,t}\right] + \theta \text{Rating}_{i,t} + \theta X_{i,t} + \epsilon_{i,t} \quad (3)$$

Figure 3 illustrates changes in EDF components by comparing firms in the highest and lowest quintiles of emissions. The findings show that asset volatility increased for firms in the highest quintile of absolute emissions between 2016 and 2018, though this effect appears to dissipate in subsequent years. For carbon intensity, a sharp increase is observed as early as 2011, which helps explain the results presented in Table 6 and aligns with the idea that emissions efficiency was more relevant before the Paris Agreement. In terms of market value, a notable decline is observed in 2015 and after 2019 for firms with high absolute emissions. For default points, neither total direct emissions nor emission intensity exhibit meaningful changes.[13]

Overall, we document the impact of emissions on firms' default probability by isolating their effects on each EDF component. The next section examines how emissions affect EDFs differently across jurisdictions —specifically, the United States, European Union, and Great Britain— leveraging cross-country variation in policy and regulatory implementation.

[13] Figure A4 presents the effects on market value of assets and default point in levels. The contrasting results relative to the log specification arises from the strong skewness in the distribution of both variables. High emitters tend to have higher absolute levels. Consequently, level regressions may mask the relative underperformance of high emitters in percentage terms after the Paris Agreement —a pattern consistent with increased market penalization of emissions.

4.5. Geographic Areas

In this section, we examine whether a firm's geographical location influences the relationship between climate and credit risk. Regional differences in the impact of transition risk on credit risk are well-documented. Evidence discussed in the literature suggests that jurisdictions with stricter regulations tend to experience heightened effects of transition risks on credit outcomes (see, for example, (Seltzer *et al.*, 2022) for U.S. firms).

Table 7 presents estimated coefficients for the United States, Euro Area, and Great Britain across three EDF horizons. All specifications include firm-level controls, as well as year and sector fixed effects. Country fixed effects are included only for firms within the European Union, where multiple countries are represented.

The results reveal distinct regional patterns across all horizons. For the United States, no statistically significant correlation is found between emissions and EDF. In contrast, European Union firms exhibit a significant positive correlation between both absolute emissions and emission intensity and EDF, consistent with the findings of Capasso *et al.* (2020). In the United Kingdom, absolute emissions are positively and significantly associated with EDF, but no significant relationship is observed for emission intensity.

Regional heterogeneity in the credit impact of climate risk likely stems from policy differences, such as the EU's established Emission Trading Scheme compared to the historically fragmented approach in the US, highlighting differences in the regulatory and market landscapes faced by firms across these regions. For instance, the EU ETS trading system, established in 2005, imposes heightened credit risks on large polluters by capping total emissions and penalizing excess pollution. By comparison, the United States operates only limited cap-and-trade systems, restricted to a few states. The disparate results likely reflect varying levels of regulatory commitment and enforcement, as well as heterogeneous firm responses to climate-related pressures and market signals.

In the appendix, we test how policy stringency affects credit risk. Table B8 reports results for the interaction of monthly carbon price surprises measured as the euro change in carbon

Table 7. Results by Geographical Location

Panel A:	1-Year EDF					
Country	**US**		**EU**		**UK**	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	-0.009		0.020*		0.023*	
	(0.010)		(0.011)		(0.014)	
Carbon Intensity		0.008		0.025***		0.013
		(0.011)		(0.009)		(0.015)
Obs	125,075	125,075	62,875	62,875	25,605	25,605
R^2	0.21	0.21	0.22	0.23	0.25	0.25
Panel B:	5-Year EDF					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	-0.012		0.032**		0.036*	
	(0.013)		(0.015)		(0.020)	
Carbon Intensity		0.010		0.038***		0.013
		(0.014)		(0.013)		(0.022)
Obs	125,075	125,075	62,875	62,875	25,605	25,605
R^2	0.24	0.24	0.25	0.26	0.31	0.31
Panel C:	10-Year EDF					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	-0.021		0.023		0.017	
	(0.014)		(0.015)		(0.019)	
Carbon Intensity		0.005		0.034***		0.009
		(0.015)		(0.012)		(0.022)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y	Y
Obs	125,075	125,075	62,875	62,875	25,605	25,605
R^2	0.36	0.35	0.38	0.38	0.49	0.49

Note: The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The sample spans the years from 2008 to 2022. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level. Statistical significance is reported as * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

price relative to prevailing wholesale electricity prices (Känzig, 2023). We set the carbon price surprise to one if there is a positive carbon price shock in a given month and zero otherwise. Since the EU ETS trading scheme operates exclusively in Europe, this analysis is restricted to that geographical area.[14]

Column (1) shows that companies with higher absolute emissions face increased credit risk during months with carbon price surprises. No statistically significant effects are observed for other horizons, which is expected as the variable is measured daily and aggregated monthly, making the effect short-term in nature. Furthermore, the results appear specific to absolute emissions rather than emission intensity, aligning with the structure of the EU ETS that enforces a fixed cap on total emissions, primarily penalizing absolute emissions rather than emission intensity.

5. Robustness

We begin by assessing the sensitivity of our results to data preprocessing choices by varying the winsorization threshold. We then conduct a broader set of robustness checks to evaluate the stability of our findings. Specifically, we examine the relationship between credit risk and multiple proxies for transition risk, incorporating Trucost's carbon earnings-at-risk metric and the announcement of science-based targets to better capture the forward-looking dimension of climate transition exposure. As part of our robustness strategy, we also re-estimate the EDF decomposition using an alternative methodology based on Structural Equation Modeling (SEM). Furthermore, we replicate the analysis across several subsamples, segmented by credit ratings, sectoral greenness, and public ownership status.

[14] Note that we use the carbon price surprise as a shock variable because the implementation of the EU ETS in 2005 predates our dataset, the second phase in 2008 coincides with our first year, and the third phase in 2013 is very close to the Paris Agreement.

Varying winsorization threshold. To ensure that our results are not unduly influenced by large issuers or extreme observations that could distort the relationship between emissions and credit risk, we apply a 5% winsorization in the main analysis. This approach limits the impact of outliers and helps to reveal underlying patterns in the data. To verify the robustness of our findings to this choice, we replicate the analysis using a stricter 1% winsorization. The core results remain broadly consistent across both thresholds, confirming that our conclusions are not driven by a small set of extreme values. The only meaningful difference appears in the exploratory analysis of carbon intensity, where statistical significance weakens under the 1% threshold—suggesting that the previously observed effect may be attributable to a handful of extreme observations. Other key results, including those related to EDF levels, ratings, and regional variation, remain stable under both winsorization choices, reinforcing the credibility of our empirical findings. All tables underlying this robustness check are available from the authors upon request, but are not reported in the paper to conserve space.

Forward Looking Risk. we replicate the analysis using carbon earnings-at-risks from Trucost. Carbon earnings-at-risk measure the additional financial cost that a company could face due to possible future carbon pricing. This is calculated for each firm based on its sector, operations, and a given price policy scenario (low, medium, and high). [15] For our analysis, we use the firm's carbon earnings-at-risks as a percentage of EBITDA, forecasted for the year 2030. Given data availability, we only have yearly data from 2017 to 2022. We choose the 2030 earnings-at-risk horizon because it allows us to exploit the 10-year EDF, both representing long-term risk. This allows us to investigate whether the EDF incorporates forward-looking transition risks. Given the sample period (2017 to 2022) and a shift in behavior after 2015, we expect carbon earnings-at-risk to be reflected in EDFs.

[15] See https://www.spglobal.com/en/Perspectives/IIF-2019/Trucost-Carbon-Earnings-at-Risk.pdf for more details.

Table 8. Forward Looking Transition Risk

	1-Year EDF			5-Year EDF			10-Year EDF		
	(1)	(2)	(3)	(7)	(8)	(9)	(13)	(14)	(15)
Log(Scope 1)	0.004	0.005	0.004	0.012	0.013	0.013	0.001	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
FWR Low	0.042**			0.057**			0.051**		
	(0.019)			(0.024)			(0.022)		
FWR Medium		0.006***			0.008***			0.007***	
		(0.001)			(0.002)			(0.002)	
FWR High			0.004***			0.005***			0.005***
			(0.001)			(0.001)			(0.001)
R^2	0.17	0.17	0.17	0.22	0.22	0.22	0.32	0.32	0.32
	1-Year EDF			5-Year EDF			10-Year EDF		
	(1)	(2)	(3)	(7)	(8)	(9)	(13)	(14)	(15)
Carbon Intensity	0.014*	0.015*	0.015*	0.023**	0.024**	0.024**	0.020*	0.021*	0.021*
	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
FWR Low	0.039***			0.052***			0.045***		
	(0.015)			(0.018)			(0.015)		
FWR Medium		0.005***			0.007***			0.007***	
		(0.001)			(0.002)			(0.001)	
FWR High			0.004***			0.005***			0.004***
			(0.001)			(0.001)			(0.001)
Year, Country and Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	54,319	54,319	54,319	54,319	54,319	54,319	54,319	54,319	54,319
R^2	0.18	0.18	0.18	0.22	0.22	0.22	0.32	0.32	0.32

Note: The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The sample spans the years from 2017 to 2022. FLR stands for Forward-Looking Risk calculated as the additional financial cost that a company could face due to possible future carbon pricing. The log(Scope 1) and 10-Year EDF variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table 8 shows a positive correlation between EDF and forward-looking transition risks (FLR) across all policy scenarios (low, medium, and high). In other words, firms facing higher future carbon pricing or regulatory pressures are associated with increased default risk. In Panel A, which uses Scope 1 emissions, the results show no statistically significant relationship with EDF, suggesting that absolute emissions alone do not fully capture forward-looking transition risks. In contrast, Panel B, which examines carbon intensity, reveals a consistently though weakly significant correlation with EDF. This effect holds across all FLR scenarios, suggesting that firms with higher carbon intensity are less efficient in their operations and more exposed to potential regulatory costs and market shifts aimed at reducing carbon footprints. In other words, the significant relationship we find between forward-looking earnings-at-risk and EDFs indicates that markets, at least partially, internalize future carbon-related earnings shocks into credit risk evaluations, providing direct evidence of investors' forward-looking climate risk pricing.

Science-based targets. A crucial aspect of transition risk involves firms' voluntary commitments to reduce their emissions. Science-based targets provide companies with a clear roadmap for cutting greenhouse gas emissions, aligned with the latest climate science and the goals of the Paris Agreement, while supporting sustainable business growth. The Science Based Targets Initiative (SBTi) includes 5,246 firms that have disclosed targets between 2014 and 2023; however, ISINs are available for only 2,084 of these firms.[16] After matching on ISIN and restricting the sample to firms with data available for the three months before and after the target publication, we retain 336 firms, 77% of which disclosed their targets after 2020. Geographically, 43% are based in the EU, 35% in the US, and 21% in the UK.

We exploit the timing of the actual publication of the targets to assess the effect on credit risk. To this end, we estimate a version of equation 2, now using firm and month-year fixed effects to absorb time shocks, and define the month prior to publication as the reference

[16] https://sciencebasedtargets.org/target-dashboard

period. We do not include credit ratings' controls due to the already limited sample size.

Table 9 presents the estimated coefficients of the interaction of emission, either absolute emissions (columns 1–3) or carbon intensity (columns 4–6), with time indicators. The estimates suggest that large emitters who set science-based targets experience a temporary reduction in EDF following the announcement. This effect is statistically significant for the 5-year and 10-year EDF, but fades within one to two months—indicating a short-lived response.

EDF decomposition: SEM. As a further robustness check, we explore the decomposition of EDF using Structural Equation Modeling (SEM). The variables employed in our decomposition are, by construction, key determinants of EDF and are inherently interrelated. Our baseline approach allows us to examine how carbon emissions influence EDF indirectly through its components. However, SEM offers a complementary framework by estimating all structural equations simultaneously and explicitly accounting for the correlations among them. This approach enables a more integrated understanding of how carbon-related variables propagate through the determinants of credit risk. The results from this alternative methodology confirm the main findings presented in the paper. Specifically, the indirect effects of emissions and carbon intensity on EDF remain statistically significant and directionally consistent with our baseline results. For transparency and completeness, we report the key outputs from the SEM analysis in Appendix Appendix B (Tables B6-B7), which present the estimated effects of carbon variables on EDF through its components. Full estimation tables are available upon request. These results reinforce the robustness of our conclusions to the choice of decomposition method.

Other measures of transition risk. Our analysis considers absolute emission levels (i.e. the long-term effect of carbon emissions) and carbon intensity (i.e. emissions relative to sales). For robustness, we replicate our initial analysis by incorporating the rate of change in carbon emissions and intensity (i.e. the short-term effect of emissions) in Table B9 and lagged values

Table 9. Changes in EDF Around Science-Based Target Announcement

	Log(Scope 1)			Carbon Intensity		
	1 Year EDF	5 Year EDF	10 Year EDF	1 Year EDF	5 Year EDF	10 Year EDF
	(1)	(2)	(3)	(4)	(5)	(6)
Emission	0.028*	0.004	-0.021*	0.001	0.008	0.007
	(0.015)	(0.014)	(0.013)	(0.013)	(0.011)	(0.008)
Emission × 3M Before	-0.004	-0.002	-0.000	0.001	-0.001	0.000
	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)
Emission × 2M Before	-0.006*	-0.004	-0.002	-0.007**	-0.004	-0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Emission × Event Month	-0.005	-0.006**	-0.005**	-0.003	-0.005***	-0.006***
	(0.003)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Emission × 1M After	-0.007	-0.006*	-0.005*	-0.006	-0.006**	-0.006**
	(0.004)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)
Emission × 2M After	-0.007	-0.006	-0.004	-0.005	-0.004	-0.004*
	(0.005)	(0.004)	(0.003)	(0.007)	(0.003)	(0.002)
Emission × 3M After	-0.006	-0.003	-0.002	-0.003	-0.003	-0.004
	(0.006)	(0.005)	(0.004)	(0.010)	(0.007)	(0.006)
Month*Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Obs	2,349	2,349	2,349	2,349	2,349	2,349
R^2	0.88	0.96	0.98	0.88	0.96	0.98

Note: The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The sample covers the period from 2017 to 2022. Emissions are measured as log(Scope 1) in columns 1–3 and as Carbon Intensity in columns 4–6. The reference month is the month before the firm publicly announces a science-based target. The log(Scope 1) and 10-Year EDF variables are winsorized at the 5th and 95th percentiles. Standard errors, clustered at the firm level, are reported in parentheses. Standard errors in parentheses are clustered at the firm level * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

in Table B10 (i.e. the temporal effect of emissions).

Table B9 in the appendix indicates that in the short-term, the carbon intensity coefficient remains positive but its effect on EDFs is not significant, as observed in the initial analysis. On the other hand, an increase in the rate of change of absolute carbon emissions today leads to a lower EDF in the short term, particularly for the 1-year horizon. This finding is consistent with expectations, as short-term changes in absolute emissions are closely linked to short-term credit risk and serve as a proxy for shifts in economic activity, which typically correspond to a lower risk of bankruptcy. In contrast, emission efficiency, as measured by carbon intensity, does not affect significantly short-term credit risk.

In Table B10, we replicate the baseline model using one-year lagged values for Scope 1 emissions and carbon intensity to deal with lagged information of emission (Zhang, 2025). The results show that carbon intensity coefficient is positive and statistically significant across all three horizons. Conversely, while the coefficients for absolute emissions are positive, we do not find a significant relationship between absolute emissions and EDFs for the 1-year and 10-year horizons. Nonetheless, there is a weakly significant positive effect on 5-year EDFs.

Breakdown by ratings, sector and public ownership. Tables B11 and B12 look at possible effects driven by Moody's credit ratings, the "greenness" of the sector, and whether a Government entity holds a majority stake in the company. We categorize firms with investment-grade ratings (from Aaa to Baa3) as "good rating" firms, and those with ratings below investment grade (Baa1 to Caa3) as "bad rating" firms.

The results reveal a negative association between absolute emissions and EDFs across all three horizons for investment-grade firms, where higher emissions is significantly associated to lower EDFs at the 1% level. In contrast, no statistically significant relationship is observed between credit risks and a firm's classification as belonging to a "green" or "brown" sector except for a weak positive effect of emissions on EDFs for firms in the most polluting sectors.

This indicates that sector-wide environmental attributes do not substantially influence EDF in this context, possibly reflecting heterogeneity in regulatory pressures or operational efficiency.[17] Finally, among firms with majority government ownership, emissions are positively associated with credit risk. This finding suggests that public ownership introduces dynamics that amplify the perceived risks of emissions. Potential explanations include inefficiencies in publicly managed operations, heightened regulatory exposure, or market expectations of government accountability for environmental performance.

Interestingly, when focusing on emissions intensity, we observe a similar effect for public ownership, which indeed reflect the fact that public ownership amplifies the financial risks associated to higher emissions, regardless of whether the metric is measured in absolute or intensity terms. We do not find any effect for rating, whether investment-grade or non-investment-grade. Finally, in the case of carbon emissions, sectoral differences in emissions intensity present a more differentiated picture. Firms in "brown" industries are associated with a higher probability of default for all EDF horizons. Conversely, firms in green industries remain mostly insulated from such risks.

6. Conclusions

We employ a comprehensive yet straightforward approach to estimate the effect of carbon emissions on credit risk. In our initial analysis, we test the relationship between absolute emissions and carbon intensity with EDFs. We find some evidence that carbon intensity is positively associated with EDFs, consistent with previous studies, although this relationship is sensitive to specification choices and driven largely by upper-tail observations. Nevertheless, our analysis identifies the Paris Agreement as a pivotal structural break, significantly increasing the sensitivity of firms' default risks to absolute emissions. Specifically, post-

[17] Green industries include consumer discretionary, consumer staples, healthcare, and telecommunications; brown industries include utilities, energy, and materials sectors.

2015, firms with high total direct emissions became riskier, primarily due to increased asset volatility.This finding highlights the importance of international climate agreements as catalysts for market perception shifts and evolving market expectations related to climate policy developments

We also provide evidence that a firm's geographical location influences the relationship between climate risk and credit risk. Regional differences in the impact of transition risk on credit outcomes are well-documented, and our findings align with prior expectations. US firms exhibit different relationships compared to EU firms, reflecting their divergent approaches to climate mitigation policies and carbon emissions regulation.

Finally, we document how firm-level heterogeneity affects the estimated relationship. We find that the impact of emissions on credit risk is stronger for high emitters, firms in "brown" sectors, and those with substantial public ownership.

In summary, our study provides empirical evidence that climate transition risks have become increasingly influential in shaping corporate default probabilities, particularly following the Paris Agreement. We show that absolute emissions became significantly correlated with EDFs after the Agreement, primarily through increased asset volatility. While our reduced-form approach does not allow precise quantification of the magnitude of these effects, we believe it offers important insights into how transition risks impact financial stability. Future work could quantify these impacts more precisely by employing structural models. Despite its simplifying assumptions, our analysis provides novel and insightful implications for both academics and policymakers.

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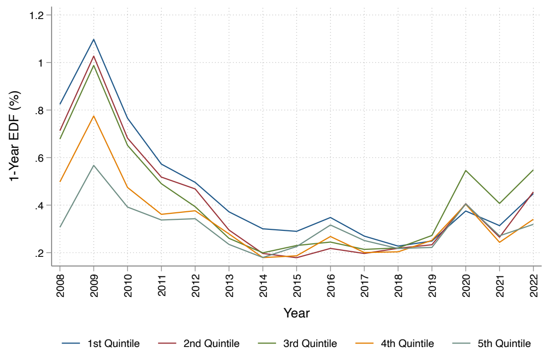
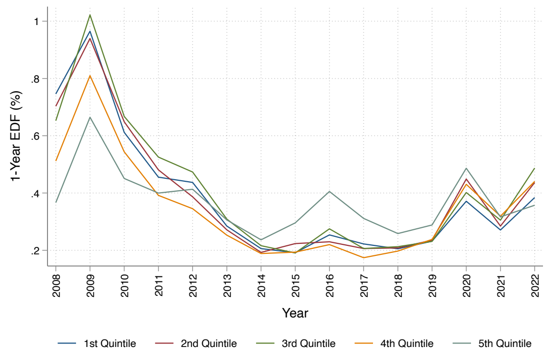
Appendix A. Appendix Figures

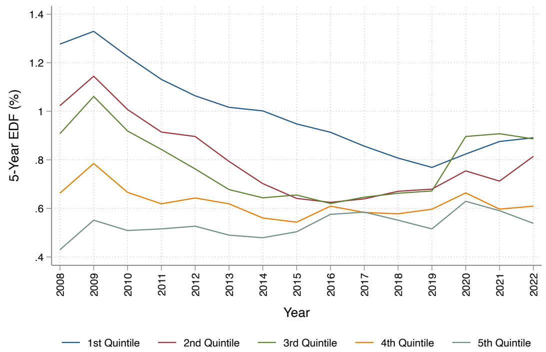
Figure A1. Time-series EDF by quintiles of total emissions and emission intensity



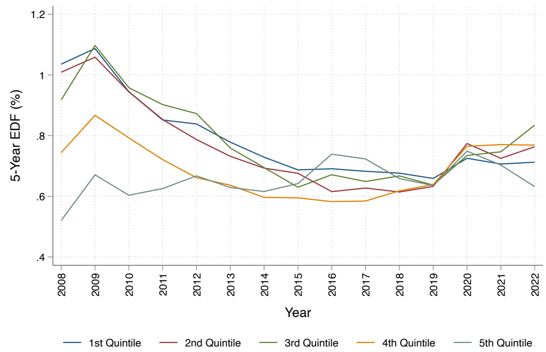
(a) Total Emission & 1-Year EDF



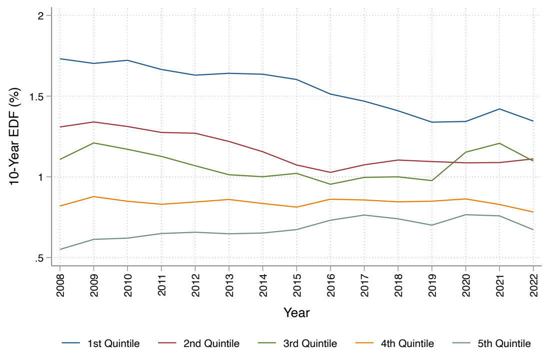
(b) Carbon Intensity & 1-Year EDF



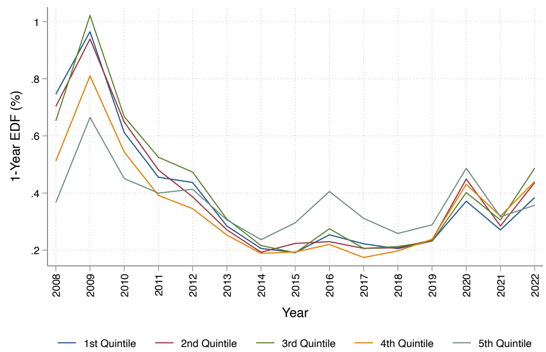
(c) Total Emission & 5-Year EDF



(d) Carbon Intensity & 5-Year EDF

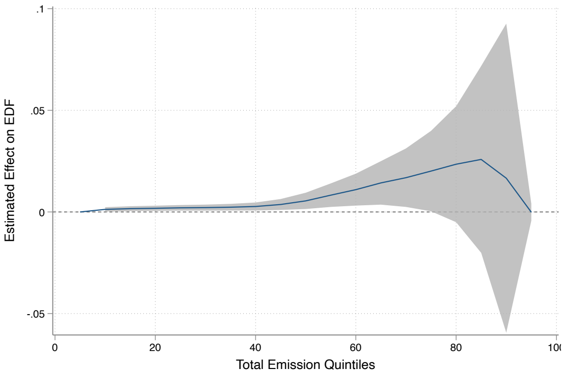


(e) Total Emission & 10-Year EDF

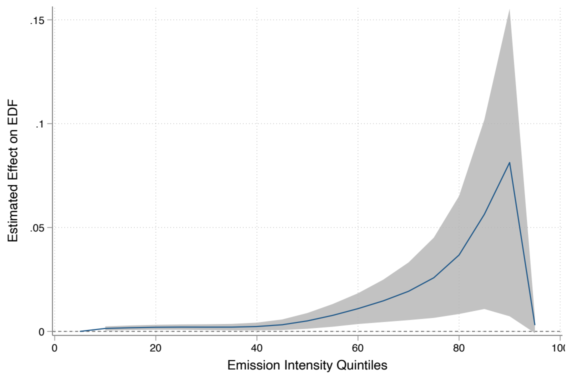


(f) Carbon Intensity & 10-Year EDF

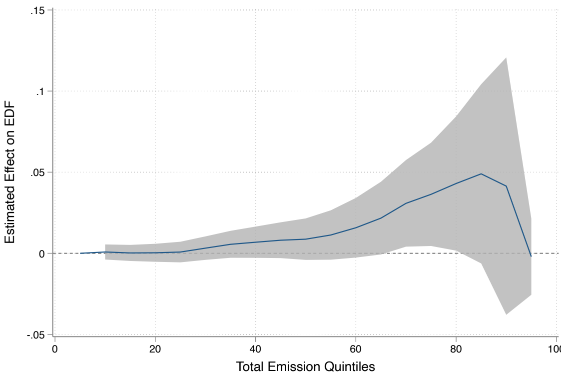
Figure A2. Analysis using Quantile Regression



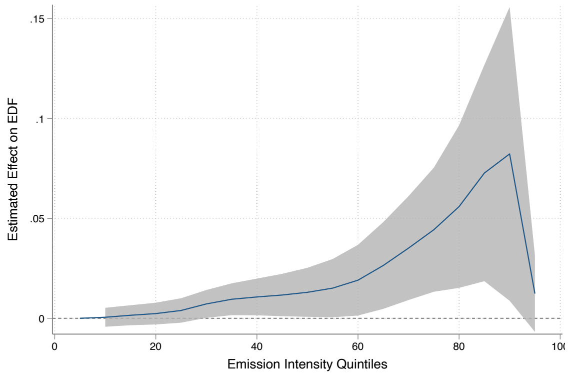
(a) 1-Year EDF & Total Emission



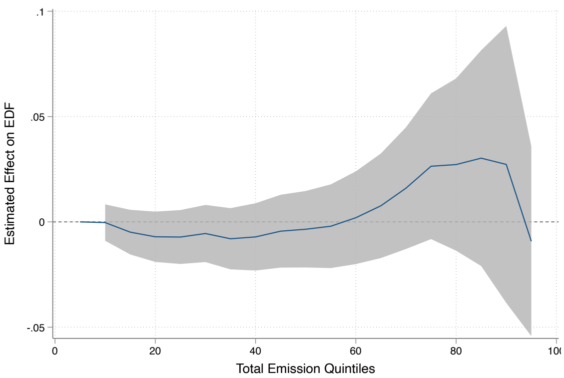
(b) 1-Year EDF & Carbon Intensity



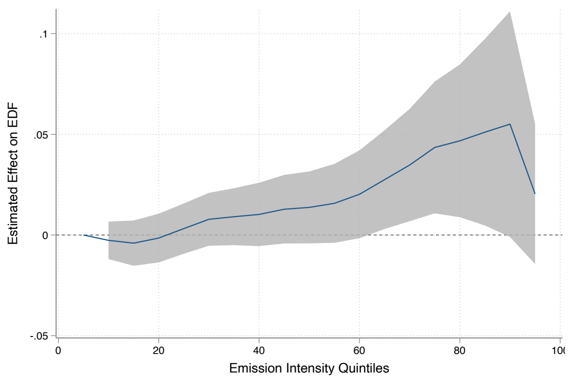
(c) 5-Year EDF & Total Emission



(d) 5-Year EDF & Carbon Intensity



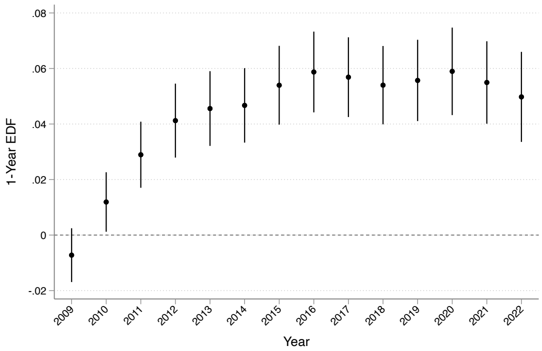
(e) 10-Year EDF & Total Emission



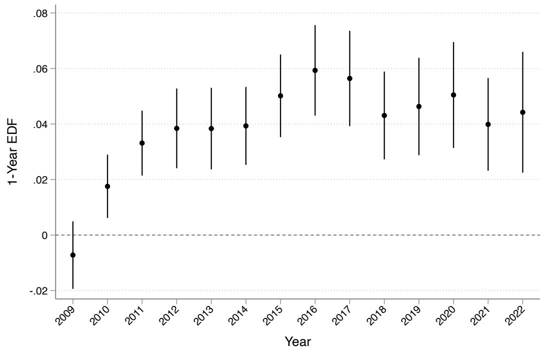
(f) 10-Year EDF & Carbon Intensity

Note: the figure presents the quintile regression of absolute emissions (left column) and carbon intensity (right column) on 1-year, 5-year, and 10-year EDFs. Coefficients are estimated running the specification (1) with all controls and year, country, and sector fixed effects. Standard errors are clustered at the firm level with 95% confidence intervals displayed.

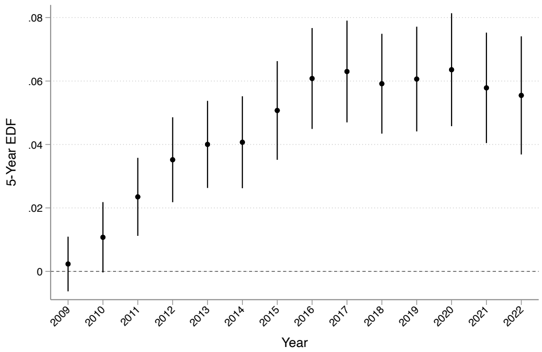
Figure A3. EDF change around Paris Agreement (without controlling for Moody's ratings)



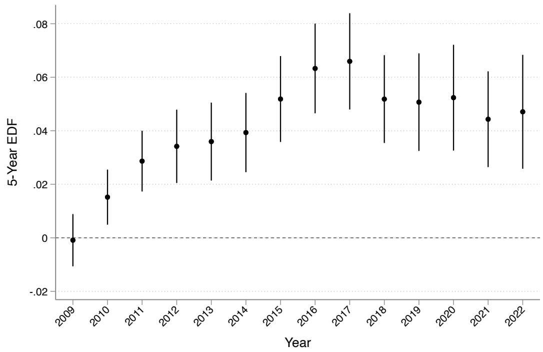
(a) Total Emission & 1-Year EDF



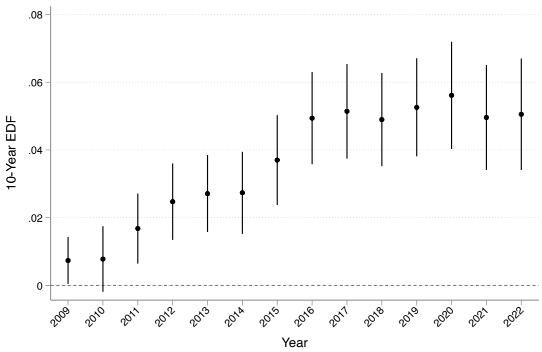
(b) Carbon Intensity & 1-Year EDF



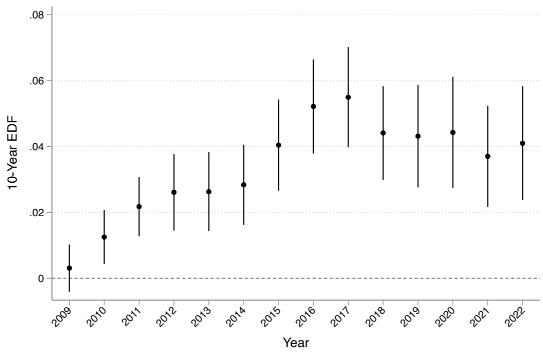
(c) Total Emission & 5-Year EDF



(d) Carbon Intensity & 5-Year EDF



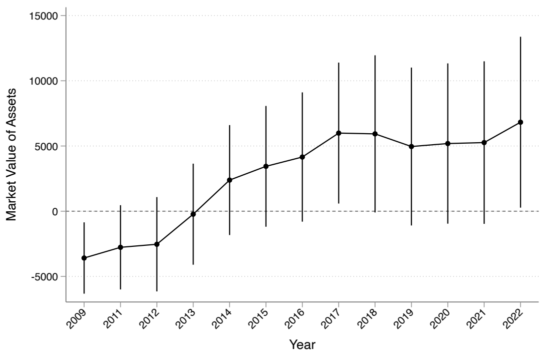
(e) Total Emission & 10-Year EDF



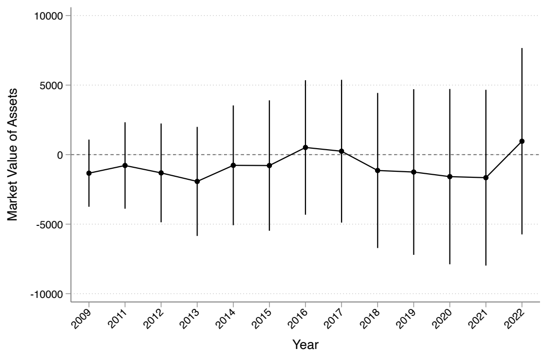
(f) Carbon Intensity & 10-Year EDF

Note: the figure presents yearly interaction coefficients of absolute emissions (left column) and carbon intensity (right column) with 1-year, 5-year, and 10-year EDFs. The base year is 2008. Coefficients are estimated using firm and year-fixed effects, with 95% confidence intervals displayed.

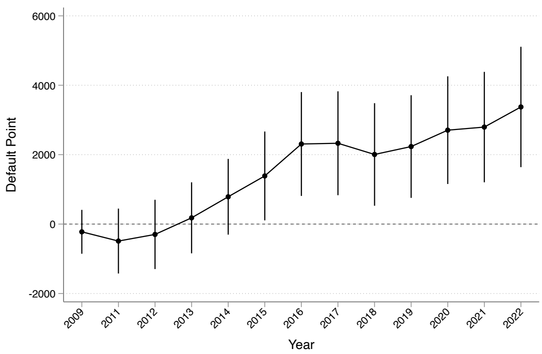
Figure A4. Difference in EDF Components Between Top and Bottom Emission Quintiles (in Levels)



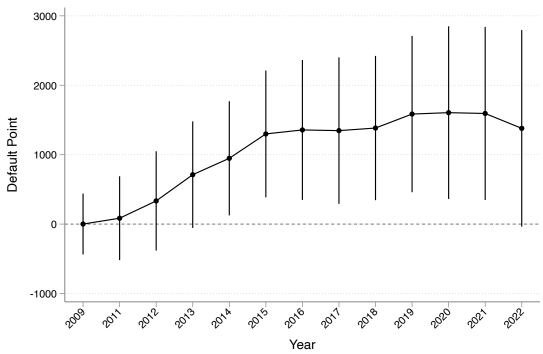
(a) Market Value Assets & Absolute Emission



(b) Market Value Assets & Carbon Intensity



(c) Default Point & Absolute Emission



(d) Default Point & Carbon Intensity

Note: the figure presents differences in market value of assets and default point (both in levels) between firms in the top and bottom quintiles of emissions. Panels compare absolute emissions (left column) and carbon intensity (right column), with estimates including country, sector and year-fixed effects. The 95% confidence intervals are also displayed.

Appendix B. Appendix Tables

Table B1. Source and Description Variables

Variable Name	Description	Source
1-Year EDF	1-Yr EDF (%)	CreditEdge
5-Year EDF	5-Yr EDF (%)	CreditEdge
10-Year EDF	10-Yr EDF (%)	CreditEdge
Mean CDS Spreads	Mean monthly CDS spreads	Refinitiv
Carbon Intensity	Carbon Intensity Scope 1+2 (t/ USD in million sales)	MSCI
Ln(scope 1)	ln(Scope 1 Emissions)	MSCI
Size	ln(Total Assets)	CRSP/Compustat
Debt Ratio	(current liabilities + long-term debt)/Total assets	CRSP/Compustat
Operating Margin Ratio	Operating income/Sales	CRSP/Compustat
Country	Country of the firms	EDF-MSCI
Sector	Sector from 2-digits NAICS code of the firms	EDF-MSCI
Year EDF	Year	EDF
Asset Volatility	Asset Volatility (EDF) (%)	CreditEdge
Market Value of Assets	Market Value of Assets (EDF)	CreditEdge
Default Point	Default Point (EDF)	CreditEdge
Moody's Ratings	Clean Moody's Ratings: encoded from 1 for AAA to 21 for C	CreditEdge
Derived CDS Ratings	Clean derived CDS Ratings: encoded from 1 for AAA to 21 for C	CreditEdge
Capital Intensity	Property, Plant and Equipment divided by Total Assets	CRSP/Compustat
Intangible Assets	Intangible Assets over Total Assets	CRSP/Compustat
Public Ownership	The indicator takes value 1 if the ultimate owner is a public entity	Orbis

Note: All CRSP/Compustat variables are expressed in USD millions.

Table B2. Analysis using Emission Levels and Intensity (not winsorized)

Panel A	1-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.039***		-0.009	
	(0.010)		(0.021)	
Carbon Intensity		-0.003		0.004
		(0.004)		(0.005)
R^2	0.05	0.05	0.10	0.10
Panel B	5-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.072***		-0.022	
	(0.009)		(0.017)	
Carbon Intensity		-0.008***		0.004
		(0.003)		(0.004)
R^2	0.06	0.03	0.16	0.16
Panel C	10-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.118***		-0.007	
	(0.008)		(0.014)	
Carbon Intensity		-0.014***		0.000
		(0.003)		(0.003)
R^2	0.12	0.03	0.27	0.27
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	N	Y	Y
Obs	213,555	213,555	213,555	213,555

Note: the controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and log sales in the current year. The dependent and independent variables are not winsorized. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table B3. Quantile Regression

Panel A	1-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.008***		0.005***	
	(0.001)		(0.002)	
Carbon Intensity		-0.003*		0.005***
		(0.002)		(0.002)
R^2	0.01	0.00	0.21	0.21
Panel B	5-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.051***		0.009	
	(0.004)		(0.007)	
Carbon Intensity		-0.026***		0.013**
		(0.006)		(0.006)
R^2	0.06	0.01	0.23	0.23
Panel C	10-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.108***		-0.003	
	(0.005)		(0.009)	
Carbon Intensity		-0.054***		0.014
		(0.008)		(0.009)
R^2	0.13	0.02	0.31	0.31
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	N	Y	Y
Obs	213,555	213,555	213,555	213,555

Note: the controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and log sales in the current year. The dependent and independent variables are winsorized at the top and bottom 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table B4. Pre and Post Paris Agreement for Total Emission

	(1) 1 Year EDF	(2) 5 Year EDF	(3) 10 Year EDF	(4) Asset Volatility	(5) Market Value of Assets	(6) Default Point
Log(Scope 1)	-0.063***	-0.072***	-0.076***	-0.396**	0.026*	0.024***
	(0.013)	(0.015)	(0.014)	(0.166)	(0.014)	(0.009)
Year 2009 × Log(Scope 1)	-0.004	-0.002	-0.001	-0.038	0.005	0.005*
	(0.010)	(0.008)	(0.006)	(0.042)	(0.004)	(0.003)
Year 2010 × Log(Scope 1)	0.009	0.002	-0.003	0.067	-0.006	0.008**
	(0.011)	(0.009)	(0.008)	(0.058)	(0.005)	(0.004)
Year 2011 × Log(Scope 1)	0.024**	0.017	0.009	0.232***	-0.012**	0.002
	(0.011)	(0.011)	(0.009)	(0.069)	(0.005)	(0.004)
Year 2012 × Log(Scope 1)	0.039***	0.029***	0.019**	0.327***	-0.015**	0.006
	(0.012)	(0.011)	(0.009)	(0.076)	(0.006)	(0.004)
Year 2013 × Log(Scope 1)	0.040***	0.031***	0.018*	0.395***	-0.023***	0.005
	(0.011)	(0.011)	(0.009)	(0.082)	(0.006)	(0.004)
Year 2014 × Log(Scope 1)	0.037***	0.033***	0.022**	0.487***	-0.022***	0.005
	(0.011)	(0.011)	(0.010)	(0.085)	(0.007)	(0.004)
Year 2015 × Log(Scope 1)	0.050***	0.050***	0.037***	0.582***	-0.025***	0.004
	(0.012)	(0.012)	(0.011)	(0.090)	(0.008)	(0.005)
Year 2016 × Log(Scope 1)	0.074***	0.074***	0.059***	0.736***	-0.017**	0.005
	(0.013)	(0.013)	(0.011)	(0.091)	(0.008)	(0.005)
Year 2017 × Log(Scope 1)	0.064***	0.077***	0.063***	0.815***	-0.019**	0.000
	(0.013)	(0.013)	(0.012)	(0.092)	(0.009)	(0.005)
Year 2018 × Log(Scope 1)	0.057***	0.066***	0.054***	0.735***	-0.025***	-0.004
	(0.012)	(0.013)	(0.012)	(0.093)	(0.009)	(0.005)
Year 2019 × Log(Scope 1)	0.066***	0.073***	0.062***	0.523***	-0.034***	-0.001
	(0.013)	(0.014)	(0.013)	(0.092)	(0.009)	(0.005)
Year 2020 × Log(Scope 1)	0.058***	0.066***	0.059***	0.204**	-0.031***	-0.004
	(0.013)	(0.015)	(0.013)	(0.092)	(0.010)	(0.005)
Year 2021 × Log(Scope 1)	0.046***	0.055***	0.048***	0.095	-0.039***	-0.008
	(0.012)	(0.014)	(0.013)	(0.095)	(0.010)	(0.005)
Year 2022 × Log(Scope 1)	0.041***	0.048***	0.045***	0.143	-0.030***	-0.013**
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	82,848	82,848	82,848	82,847	82,847	82,847
R^2	0.41	0.48	0.54	0.88	0.97	0.98

Note: The coefficients of interest in the table are those for Log(Scope 1), the interaction between the year indicators (with 2008 as the base year) and Log(Scope 1). The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and log sales in the current year. We do not report the coefficients of the interaction between absolute emissions and years' dummies and between Moody's rating and years' dummies. The specification includes year, country and sector fixed effects. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table B5. Pre and Post Paris Agreement for Emission Intensity

	(1) 1 Year EDF	(2) 5 Year EDF	(3) 10 Year EDF	(4) Asset Volatility	(5) Market Value of Assets	(6) Default Point
Carbon Intensity	-0.039***	-0.043***	-0.042***	-0.106	0.024***	0.014**
	(0.009)	(0.010)	(0.010)	(0.092)	(0.008)	(0.006)
Year 2009 × Carbon Intensity	-0.004	-0.000	0.000	0.010	-0.002	-0.000
	(0.006)	(0.005)	(0.004)	(0.029)	(0.002)	(0.002)
Year 2010 × Carbon Intensity	0.013**	0.009	0.006	0.097***	-0.009***	0.001
	(0.006)	(0.006)	(0.005)	(0.038)	(0.003)	(0.003)
Year 2011 × Carbon Intensity	0.025***	0.020***	0.015**	0.201***	-0.010***	-0.002
	(0.007)	(0.007)	(0.006)	(0.044)	(0.003)	(0.003)
Year 2012 × Carbon Intensity	0.025***	0.021***	0.014**	0.215***	-0.008*	-0.000
	(0.008)	(0.008)	(0.006)	(0.052)	(0.004)	(0.003)
Year 2013 × Carbon Intensity	0.034***	0.025***	0.016**	0.250***	-0.014***	-0.001
	(0.008)	(0.008)	(0.007)	(0.058)	(0.004)	(0.003)
Year 2014 × Carbon Intensity	0.036***	0.031***	0.023***	0.317***	-0.016***	0.000
	(0.008)	(0.008)	(0.007)	(0.057)	(0.005)	(0.003)
Year 2015 × Carbon Intensity	0.043***	0.041***	0.031***	0.371***	-0.019***	0.000
	(0.008)	(0.009)	(0.008)	(0.061)	(0.006)	(0.004)
Year 2016 × Carbon Intensity	0.055***	0.052***	0.041***	0.502***	-0.010*	0.002
	(0.010)	(0.010)	(0.009)	(0.061)	(0.005)	(0.004)
Year 2017 × Carbon Intensity	0.058***	0.061***	0.049***	0.602***	-0.012**	-0.001
	(0.010)	(0.011)	(0.009)	(0.065)	(0.006)	(0.004)
Year 2018 × Carbon Intensity	0.045***	0.049***	0.039***	0.541***	-0.009	0.001
	(0.008)	(0.009)	(0.009)	(0.066)	(0.006)	(0.004)
Year 2019 × Carbon Intensity	0.048***	0.050***	0.041***	0.354***	-0.011*	0.003
	(0.009)	(0.011)	(0.010)	(0.061)	(0.007)	(0.004)
Year 2020 × Carbon Intensity	0.044***	0.046***	0.039***	0.104*	-0.011	0.004
	(0.010)	(0.011)	(0.010)	(0.062)	(0.007)	(0.005)
Year 2021 × Carbon Intensity	0.035***	0.039***	0.032***	0.062	-0.012*	0.003
	(0.009)	(0.011)	(0.010)	(0.067)	(0.007)	(0.005)
Year 2022 × Carbon Intensity	0.036***	0.038***	0.033***	0.139*	-0.006	-0.001
	(0.013)	(0.013)	(0.012)	(0.075)	(0.007)	(0.005)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	82,848	82,848	82,848	82,847	82,847	82,847
R^2	0.41	0.48	0.54	0.87	0.97	0.98

Note: The coefficients of interest in the table are those for Carbon Intensity, the interaction between the year indicators (with 2008 as the base year) and Carbon Intensity. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and log sales in the current year. We do not report the coefficients of the interaction between emissions and years' dummies and between Moody's rating and years' dummies. The specification includes year, country and sector fixed effects. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table B6. Effect of *Log(Scope 1)* on EDF through its components

Indirect effect	1-Year EDF	5-Year EDF	10-Year EDF
Asset volatility	0.007026***	0.008357***	0.008037***
	(0.000452)	(0.000538)	(0.000517)
Log(Market value)	0.004564***	0.005918***	0.005607***
	(0.000542)	(0.000703)	(0.000666)
Log(Default point)	0.005826***	0.007597***	0.006884***
	(0.000346)	(0.000451)	(0.000409)
Direct effect			
Log(Scope1)	0.004972***	0.009455***	0.008689***
	(0.000675)	(0.000738)	(0.000742)

Note: This table reports the direct and indirect effects of $log(Scope1)$ on EDF, using a structural equation model (SEM) that decomposes the overall effect into three EDF components (asset volatility, log(market value of assets), and log(default point)). The indirect effect is obtained by multiplying (i) the coefficient of the variable of interest (asset volatility, log(market value of assets), and log(default point)) from the main regression by (ii) the coefficient on the interaction term $log(Scope1)Post - Paris$ in the corresponding EDF-component regression. Standard errors are shown in parentheses * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table B7. Effect of Carbon intensity on EDF through its components

Indirect effect	1-Year EDF	5-Year EDF	10-Year EDF
Asset volatility	0.003983***	0.004758***	0.004619***
	(0.000597)	(0.000713)	(0.000692)
Log(Market value)	0.007917***	0.010242***	0.009639***
	(0.000708)	(0.000916)	(0.000862)
Log(Default point)	0.004169***	0.005444***	0.004941***
	(0.000449)	(0.000586)	(0.000532)
Direct effect			
Carbon intensity	0.008586***	0.014839***	0.013866***
	(0.000876)	(0.000959)	(0.000969)

Note: This table reports the direct and indirect effects of $carbon\,intensity$ on EDF, using a structural equation model (SEM) that decomposes the overall effect into three EDF components (asset volatility, log(market value of assets), and log(default point)). The indirect effect is obtained by multiplying (i) the coefficient of the variable of interest (asset volatility, log(market value of assets), or log(default point)) from the main regression by (ii) the coefficient on the interaction term $carbon\,intensityPost-Paris$ in the corresponding EDF-component regression. Standard errors are shown in parentheses * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table B8. Carbon Surprise and Credit Risk in Europe

	1-Year EDF		5-Year EDF		10-Year EDF	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)	0.017		0.030*		0.023	
	(0.012)		(0.016)		(0.015)	
CPSurprise × Log(Scope 1)	0.004**		0.002		-0.001	
	(0.002)		(0.002)		(0.001)	
Carbon Intensity		0.025***		0.037***		0.035***
		(0.009)		(0.013)		(0.012)
CPSurprise × Carbon Intensity		0.003		0.002		0.000
		(0.002)		(0.002)		(0.001)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	49,955	49,955	49,955	49,955	49,955	49,955
R^2	0.25	0.25	0.27	0.28	0.39	0.40

Note: The coefficients of interest in the table are those for Carbon Intensity and Log(Scope 1) interacted with CPSurprise. CPSurprise is a binary variable that takes value one if there is a positive carbon policy surprise and 0 otherwise. The carbon policy surprises are measured as euro change in carbon price, relative to prevailing wholesale electricity price (Känzig, 2023). The analysis is conducted for the Europe area only. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The specification includes year, country and sector fixed effects. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table B9. Rate of Change in Emissions

	1-Year EDF		5-Year EDF		10-Year EDF	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-(t-1)}$Log(Scope 1)	-0.023***		-0.016		-0.000	
	(0.009)		(0.011)		(0.011)	
$\Delta_{t-(t-1)}$Carbon Intensity		0.008		0.005		0.001
		(0.008)		(0.009)		(0.009)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	197,582	197,582	197,582	197,582	197,582	197,582
R^2	0.18	0.18	0.21	0.21	0.34	0.34

Note: The dependent variable is $\Delta log(Scope1)$ constructed as $log(Scope1)_t - log(Scope1)_{t-1}$. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales.The Fixed Effects (FE) included are Year, Country, and Sector FE. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, and statistical significance is * for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table B10. Lagged Emissions

	1-Year EDF		5-Year EDF		10-Year EDF	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Scope 1)$_{t-1}$	0.010		0.016*		0.004	
	(0.007)		(0.009)		(0.009)	
Carbon Intensity$_{t-1}$		0.017**		0.024***		0.020**
		(0.007)		(0.009)		(0.009)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	197,582	197,582	197,582	197,582	197,582	197,582
R^2	0.18	0.18	0.21	0.21	0.34	0.34

Note: The table reports the analysis using 1-year lagged emission variables. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales.The Fixed Effects (FE) included are Year, Country, and Sector FE. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, and statistical significance is reported as * for $p < 0.05$, ** for $p < 0.01$ and for *** $p < 0.001$.

Table B11. Ratings, Sector and Public Ownership (Total Emissions)

Firms breakdown	Ratings		Sector		Ownership	
	Good	Bad	Green	Brown	Public	Private
	Panel (1) - 1-Year EDF					
Log(Scope 1)	-0.016**	0.004	0.012	0.013	0.073***	0.002
	(0.006)	(0.022)	(0.019)	(0.011)	(0.024)	(0.007)
R^2	0.20	0.24	0.23	0.30	0.43	0.20
	Panel (2) - 5-Year EDF					
Log(Scope 1)	-0.022***	0.007	0.031	0.025*	0.087***	0.008
	(0.008)	(0.026)	(0.026)	(0.015)	(0.032)	(0.010)
R^2	0.26	0.21	0.26	0.41	0.57	0.22
	Panel (3) - 10-Year EDF					
Log(Scope 1)	-0.030***	-0.007	0.027	0.016	0.061**	0.001
	(0.009)	(0.025)	(0.026)	(0.017)	(0.026)	(0.010)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	52,043	30,402	34,251	26,386	6,757	180,817
R^2	0.36	0.26	0.44	0.50	0.68	0.35

Note: The table reports the estimated coefficients of the baseline regression divided by ratings, sector and public ownership with Year, Sector and Country FE. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.05$, ** for $p < 0.01$ and for *** $p < 0.001$.

Table B12. Ratings, Sector and Public Ownership (Carbon Intensity)

Firms breakdown	Ratings		Sector		Ownership	
	Good	Bad	Green	Brown	Public	Private
	Panel (1) - 1-Year EDF					
Carbon Intensity	-0.004	0.026	-0.083	0.021***	0.056***	0.011
	(0.004)	(0.024)	(0.100)	(0.007)	(0.016)	(0.008)
R^2	0.20	0.24	0.23	0.30	0.44	0.20
	Panel (2) - 5-Year EDF					
Carbon Intensity	-0.005	0.030	-0.098	0.033***	0.075***	0.016
	(0.005)	(0.028)	(0.135)	(0.010)	(0.020)	(0.011)
R^2	0.25	0.21	0.26	0.42	0.59	0.22
	Panel (3) - 10-Year EDF					
Carbon Intensity	-0.009	0.022	-0.169*	0.032***	0.061***	0.012
	(0.006)	(0.025)	(0.092)	(0.011)	(0.016)	(0.011)
Year, Country and Sector FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs	52,043	30,402	34,251	26,386	6,757	180,817
R^2	0.35	0.26	0.44	0.51	0.69	0.35

Note: The table reports the estimated coefficients of the baseline regression divided by ratings, sector and public ownership with Year, Sector and Country FE. The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. The dependent and independent variables are winsorized at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.05$, ** for $p < 0.01$ and for *** $p < 0.001$.

Table B13. Yearly Analysis of Emission Levels and Intensity

Panel A	1-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.018***		0.008	
	(0.004)		(0.007)	
Carbon Intensity		-0.005		0.016**
		(0.005)		(0.007)
R^2	0.12	0.11	0.21	0.21
Panel B	5-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.055***		0.014	
	(0.005)		(0.009)	
Carbon Intensity		-0.023***		0.022**
		(0.008)		(0.009)
R^2	0.08	0.04	0.22	0.23
Panel C	10-Year EDF			
	(1)	(2)	(3)	(4)
Log(Scope 1)	-0.103***		0.003	
	(0.006)		(0.010)	
Carbon Intensity		-0.049***		0.018*
		(0.008)		(0.009)
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Sector FE	N	N	Y	Y
Controls	N	N	Y	Y
Obs	17,909	17,909	17,909	17,909
R^2	0.16	0.04	0.35	0.35

Note: The controls included are size, debt ratio, operating margin, capital intensity, intangible assets, and current-year log sales. EDF values are reported as the average EDF at the yearly level for each company. The dependent and independent variables are winsorize at the bottom and top 5%. Standard errors in parentheses are clustered at the firm level, * for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

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