The Rise of Climate Risks: Evidence on Firms' Expected Default Frequencies

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Abstract

This paper studies the relationship between climate risk and credit risk. We find a negative correlation between emission levels and default risk once firm's fixed characteristics are taken into account. By breaking down Moody's Expected Default Frequencies (EDFs) into its main components, we are able to uncover the drivers of this result. First, we show that carbon emissions are relevant for the probability of default, especially through the asset volatility channel. Second, we provide evidence that the 2015 Paris Agreement marked a policy turning point that reverberated on firms' credit risk. After 2015, our results suggest that firms with high carbon footprints became riskier. We observe that this relation is driven by a decrease (increase) in asset volatility of small (large) emitters. With this analysis, we shed light on the channels through which climate risks affect credit risk, highlighting a number of aspects to consider when including climate risk in credit risk-related analyses.

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

JEL codes: C12, C21, C23, C31

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1. Introduction

Following the relatively recent interest attracted by climate issues, scholars have studied the effect of climate change on the economy from several different perspectives.[2] 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 firm's credit risk. Estimating this link is complicated because both variables suffer from endogeneity problems and measurement errors. Using ESG ratings as a proxy for climate risk, earlier studies show that an increase in ESG scores leads to lower CDS spreads (Barth et al., 2020), better credit ratings (Devalle et al., 2017) and lower bond's risk premia (Kotró and Márkus, 2020).

Other studies use carbon emission 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 (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 only find evidence 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 emission levels and Moody's Expected Default Frequencies (EDFs) for 1,841 firms from 2008 to 2019. Moody's EDF, a market-implied probability that a firm will default, has a series of desirable features for our analysis. First, compared to previous studies which use computed distances to default, Moody's Analytics uses proprietary actual default data to obtain physical probabilities of default. Starting from the risk-neutral distance to default obtained with an improved version

[2] For a summary of the related literature on climate finance, see Giglio et al., 2021

of Merton (1974) model, they project the computed distances to default onto actual default data, hence obtaining a linear map from the risk-neutral probabilities into physical probabilities of default. This approach has the advantage of excluding risk-aversion adjustment components which complicate the inference on the data. Second, we are able to break down the EDF 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. The EDF drivers fully explain its variability, by construction. Hence, by adopting a two-stage regression approach we can show how carbon emissions affect each identified driver of the EDF. Third, using EDF we are able to study the temporal dimension of credit risk, i.e. whether climate risks affect the probability of a firm defaulting in 1, 5 or 10 years. We find evidence of a negative relation between emissions for all horizons of credit risk (short to long-term). The results are robust to the inclusion of the firm's level controls and a series of fixed effects. In line with previous studies, we show that when looking at within industries effects, firms with higher emissions (fifth quintile of emissions) are penalized for the higher transition risk with higher credit risk. However, after the inclusion of firm fixed effects, we find that firms increasing their emissions over time are not penalized with higher credit risks.

To show that our result is not driven by our choice of credit or transition risk variables, we then repeat the analysis using variables often adopted in the literature. The choice of emission levels as independent variable of interest rest on the assumption that climate goals are set on absolute emissions, hence they are a preferable proxy of firms' transition risk (Bolton and Kacperczyk, 2021*c*). Nonetheless, in the section of the paper dealing with robustness checks, we test the consistency of the relationship between carbon emissions and the probability of default also for carbon intensity, lagged values of emission levels and the rate of carbon emission changes. The results corroborate our preliminary assumption that relative, as well as short-term measures of carbon emissions, have a weaker link with credit risk. Interestingly, when using other measures of default risks such as CDS spreads and credit ratings, the results are consistent with previous studies. In line with Carbone et al. (2021) we find that only the carbon intensities are positively associated with credit risk.

We further analyze our results by decomposing EDFs into their main components: asset volatility, the market value of assets, and default point. First, we document how each component enters linearly into the EDF. We show that higher asset volatility and default point are associated with a higher probability of default, while the market value of assets reduces default risk. Then, we analyze the effect of carbon emissions on each EDF component. We find that: i) carbon emissions affect negatively asset volatility, which is consistent with the observed negative coefficient in the baseline estimation; ii) the introduction of firm-level fixed effects determines a negative coefficient in the estimated baseline equation through the default point channel; iii) by absorbing only common cross-firm variation through industry fixed effects, the market value of assets channel largely reduces the magnitude of the coefficient in the baseline regression.

Next, we investigate whether the signing and ratification of the Paris Climate Accords marked a structural break in policies, especially from a corporate point of view. In other words, we try to explore the relevance of the Agreement as a possible determinant of an increase in credit risk through its amplifying effect on climate transition risk. Our intuition is simple: we expect that for signatory countries, bound by the agreement pledges, the probability of an increase in transition risk should rise in response to stricter climate regulation, thus increasing also the uncertainty for domestic firms. This effect should be stronger for firms in higher percentiles of the carbon emissions distribution, which could experience more difficulties coping with stricter carbon regulations. The uncertainty, then, would directly translate into higher asset volatility and consequently determine a higher EDF. In this work, we find that following the Paris Agreement, an increase in direct emissions leads to an increase in the probability of default for firms within the same credit rating class. When looking at the EDF components, we document that the increased default risk of large emitters is driven by an increase in asset volatility after the Paris Agreement.

To the best of our knowledge, this is the first paper in the related literature that uses Moody's Analytics EDFs to proxy the probability of default and that provides insights into the transmission channel of climate risks on firm-level credit risk. [3] This study complements the existing literature in two key aspects. First, we document a negative relation between climate and credit risks once a physical probability of default is taken into account and firm fixed characteristics are controlled for. This relationship however vanishes after the structural break of the 2015 Paris Agreement and the consequent rise in investors' awareness of climate risks. Second, we single out the channels by which carbon emissions affect firms' probability of default. Indeed, the increase in the credit risk of firms with large carbon footprints is mainly driven by higher asset prices uncertainty. While our approach does not allow us to say much about the magnitude of the effects we unveiled, we believe that this study opens the way to future research in which a structural model is used to pin down the magnitudes of the effects we uncovered.

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

Earlier studies coped with this problem by using corporate social responsibility 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) 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 of ESG scores leads to lower

[3] Acharya et al. (2022) use Moody's EDFs to show that heat stress exposure increases credit risk of municipal as well as corporate bonds.

CDS spreads (Barth et al., 2020), better ratings by Moody's (Devalle et al., 2017), lower bond's risk premia (Kotró and Márkus, 2020). Similar to Höck et al. (2020), Barth et al. (2020) conclude that higher ESG ratings correlate with lower credit risk (proxy by CDS spreads), with a stronger effect for European firms and firms with medium ESG ratings.[4]

One of the criticisms often made to the use of ESG data is that they are unstandardized, non-compulsory and not fully transparent in how they are constructed (see, for example, Berg et al., 2020). Thus, making it hard to disentangle the drivers of their effect on credit risk.

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 emission. 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, it is important to point out that there is a recent strand of literature that centers around the construction of climate-corrected ratings. Kölbel et al. (2020) 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. (2021) construct a model similar to

[4]Another relevant paper belonging to this strand of literature is Henisz and McGlinch (2019) which using RavenPack's reported news show that previous years' higher ESG ratings have a strong correlation with lower future assets volatility.

S&P's such as to incorporate climate physical risks into sovereign ratings for possible future climate scenarios. Sautner et al. (2020) use quarterly earnings calls to construct an annual firm-level measure of firms' exposure to climate. Further work will consist in using one of these novel firms' climate exposure variables to further corroborate our findings.

Our paper proceeds as follows. First, we present the data and the methodology in more detail in the following section: we describe the dataset and provide information on how data are treated in order to construct the sample; then we set out the methodology adopted to obtain a robust estimate of the relationship under scrutiny. Next, in Section 3 we describe the sample providing the first descriptive evidence of the relationship between carbon emissions and the probability of default. In Section 4, we present empirical evidence by testing the relationship under review. This section also includes a thorough robustness analysis to test the consistency of the results obtained. Finally, Section 5 concludes the paper.

2. Data and Methodology

2.1. Data

The dataset is constructed by gathering data from four different 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 are from CRSP and Compustat.

Our starting sample includes all firms with yearly carbon emissions in MSCI for the main advanced economies: United States, United Kingdom, Eurozone and Japan from 2008 to 2019. We match the data with Moody's CreditEdge to obtain Expected Default Frequencies (EDFs) and Moody's credit ratings. We add balance sheet data taken from Compustat Global and CRSP/Compustat in WRDS.[5]

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

We also collect 5-year single-name CDS spreads for unsecured debt with the "Modified Modified Restructuring" clause (MM14) from 2008 to 2019. All CDS spreads are in US dollars. Following Gao et al. (2020) the data are aggregated at the monthly level by taking the mean over the month within each entity. For robustness, we replicate the analysis with the median and end-of-the-month CDS spreads. We discard all CDSs with spread greater than 4000 basis points (Zhang et al., 2009) and illiquid CDS (Blasberg et al., 2021).

As part of the strategy to identify the effect of climate on firms' credit risk, we apply several filters to the sample analyzed. We start by winsorizing the distribution of the sample at the 1% level to avoid results driven by a few extremely high carbon emitters or emitters incorrectly reporting zero emissions. The second filter drops observations with missing accounting and financial data. Of the remaining firm-month observations in the sample, we discard firms with less than 7 years of complete data. Finally, we exclude from our analysis firms with a primary SIC code between 6000 and 7000 which include financial firms and insurance companies, and also firms belonging to the public administration and other services sectors in order to avoid misinterpretation of the outcomes driven by the largely different financial behavior of these entities.

The final dataset includes 1,841 firms over 2008-2019 with monthly EDFs, monthly CDS Spreads (for 16% of the firms), quarterly balance sheet information and yearly carbon emissions.[6]

2.2. Methodology

In the main specification, the dependent variable is defined alternatively as the EDF at the 1-year, 5-year and 10-year horizon. The EDF quantifies the probability that a firm will default within the specified time, respectively 1-year, 5-year, or 10-year.

In each specification, the dependent variable is regressed on the logarithm of firms' yearly

[6] In terms of CSPP representatives, the sample includes 39% (138 out of 352) of the companies eligible in the CSPP at the date of the collection. Of those 138 firms, 27% (78 out of 138) also have CDS spreads.

level of Scope 1 carbon emissions. The choice of using only direct emission levels stems from recent literature highlighting how investors' preferences are driven by emission levels more than the intensity, given that carbon emission policy aims at zero-carbon emissions (see, Bolton and Kacperczyk, 2021*a*). We apply the high-dimensional fixed effects estimation methodology described in Guimaraes and Portugal (2010). Our baseline regression equation is the following:

$$EDF_{it} = \alpha + \beta_1 * Log(Scope1)_{it} + \beta X_{it} + FE + \epsilon_{it} \tag{1}$$

where the dependent variable is monthly EDF_{it}, the independent variable is yearly $Log(Scope1)_{it}$ and X_{it} is a set of firms' control variables. Specifically, we include firm size measured as the logarithm of the firm's total assets, the debt ratio, the operating margin ratio and the capital intensity of the firm. Since the probability of default may be driven by several firm-specific factors, we use these factors as control variables to isolate the effect of the climate variable on the probability of default of each firm. FE is the matrix of country, industry and calendar-year levels of fixed effects. For example, year-fixed effects would control for the 2007-2008 financial crisis that led to a spike in the firm's probability of default. We also include firm fixed effects to account for observable and unobservable characteristics at the firm level. Finally, following the literature, we cluster standard errors at the firm level.

3. Descriptive Statistics

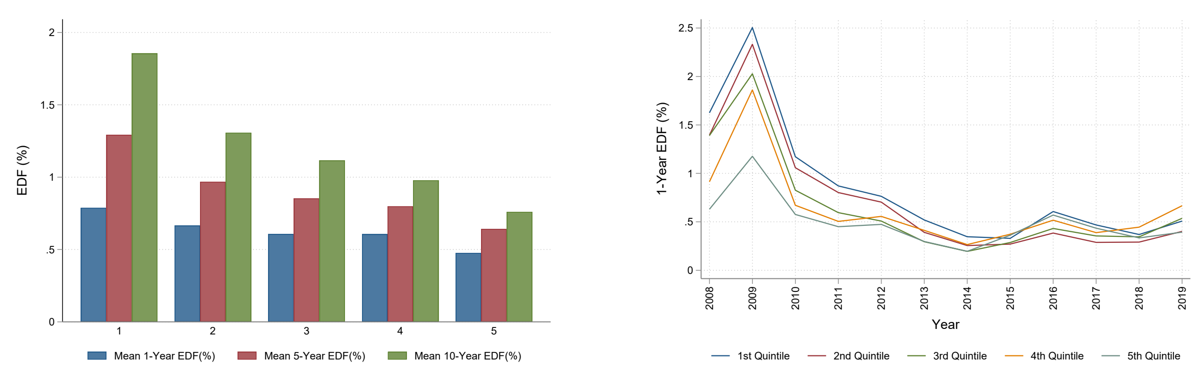
The sample comprises 1,841 firms with a wide coverage at the geographical and sector level. In terms of geographical variation, the sample includes 67% of firms from the United States, 22% from the Euro Area, 10% from the United Kingdom and 0.4% from Japan. Across industries, approximately 46% of the companies are from the manufacturing sector followed by 9% in the information sector. The lowest number of firms is found in sectors such as agriculture, management of companies, education and arts.

Table 1. Summary Statistics

	Mean	Median	SD	Min	Max	Observation
1 Year EDF (%)	0.63	0.10	1.78	0.01	28.83	243886
5 Year EDF (%)	0.91	0.46	1.24	0.06	11.36	243886
10 Year EDF (%)	1.20	0.86	1.12	0.12	7.67	243886
Mean CDS Spreads	145.06	80.63	208.40	15.64	2885.58	36234
Carbon Intensity	238.14	36.10	684.70	1.30	5632.00	243889
Ln(scope 1)	10.40	10.21	2.99	3.22	18.04	243721
Size	7.86	7.77	1.72	0.62	15.54	243886
Debt Ratio	0.27	0.25	0.22	0.00	6.04	243646
Operating Margin Ratio	-3.21	0.32	285.79	-70046.99	6708.00	233779
Asset Volatility	23.52	21.08	11.06	2.45	96.75	243886
Market Value of Assets	18173.21	4065.37	52624.41	8.76	1578809.25	243886
Market Leverage	27.79	24.49	17.97	0.00	99.99	243886
Default Point	5126.00	981.68	16954.37	0.08	532462.94	243886
Moody's Ratings'	10.49	10.00	3.57	1.00	21.00	93796
Derived CDS Ratings	8.27	8.00	4.08	1.00	21.00	46869
Capital Intensity	0.26	0.19	0.23	0.00	1.00	243256
Book Value Equity	4328.51	868.60	13604.54	-17577.00	201442.00	170025
Research And Development	0.02	0.01	0.03	-0.00	1.13	108260
Intangible Assets	0.22	0.16	0.21	0.00	1.10	169881

Note: 1-Year EDF, 5-Year EDF, 10-Year EDF, 5-Year CDS Spreads, Scope 1 Emission and Carbon Intensity are winsorized at the bottom and top 1%. See Table A1 for variables' description and sources.

Figure 1. Mean EDF by quintile of Log(Scope 1)



(a) Full Sample

(b) Over Time for 1-Year EDF

Table 1 reports the summary statistics for the main variables of our analysis. The average firm in our sample has a probability of default in one year of 0.63% with a debt ratio of 27%.[7] As expected, we notice a positive term structure of the EDF, i.e. 10-year EDF has a larger mean and lower standard deviation (1.20% and 1.12%) compared to 5-year EDF (0.91% and 1.24%) and 1-year EDF (0.63% and 1.78%).

Figure 1 (a) presents the average EDF for respectively 1-year, 5-year and 10-year EDF divided by emission quintiles, while Figure 1 (b) reports the time series of 1-year EDF from 2008 to 2019. In panel (a) for every horizon of emission, we observe that firms in higher quintiles (large emitters) have a lower probability of default with respect to firms in the first quintile. We deem this figure as particularly striking given the common prior that firms with higher carbon footprints are penalized by the market. However, panel (b) shows that the average 1-year EDF for firms in the top quintiles rapidly increased after 2015. This is in line with previous studies that document the remarkable impact of the 2015 Paris Agreement in shaping investors and policymaker perception of firm's riskiness (Bolton and Kacperczyk, 2021*b*; Carbone et al., 2021; Capasso et al., 2020; Seltzer et al., 2022; Barth et al., 2020; Kölbel et al., 2020). By computing a two-sample t-test we confirm that the average 1-year EDF for firms in the bottom quintile is not statistically different from firms in the top quintile between 2015 and 2019. These two means, however, return again statistically different in 2019.[8]

[7] See Table A1 for an in-depth description of the variables used in the analysis.

[8] In the Appendix, Figure A1 panel (a) replicates Figure 1 (a) using quintiles of carbon intensity (relative emissions). Figure A1 panel (a) shows that a negative relationship between emissions and credit risks is present only for the long-term horizon, i.e. 10-year EDF. This first graphical evidence suggests that, at least for the short and medium-term horizon, there is no evidence of a difference between high and low-carbon emitters once we adjust for the firm's size. Figure A1 (panels b-f) also reports the time series for 1,5 and 10-year EDF for different quintiles of carbon emission, both in level and relative terms.

4. Results

4.1. Baseline Result

In this section, we pose the foundations of the analysis by estimating the baseline regression equation separately for the three different EDF horizons. In Table 2 we report the estimated coefficients for the baseline equation described in the previous section. Column 1 includes year and country fixed effects, column 2 adds industry fixed effects while column 3 adds firm fixed effects. Column 4 to 6 include also firm-level controls. For reasons of space, we do not report the coefficients of the control variables.

The results in Table 2 show evidence of an effect of climate risk on credit risk. The relevant coefficients in all columns are statistically significant. Nonetheless, compared to the existing literature, we find an opposite effect of the climate variable on credit risk. Indeed, negative coefficients suggest that higher emissions for a firm imply a lower probability of default, even after controlling for a large number of confounding factors. Starting from column 1 the coefficients indicate that for every 1% increase in the level of emissions, the 1-year EDF decreases by 0.0345 p.p., while the 5 and 10-year EDF decrease by 0.0751 and 0.127 p.p., respectively. The effect increases in magnitude with the inclusion of industry-fixed effects (column 3) and firm-fixed effects (column 4). More interestingly, the inclusion of firm-level controls in columns 4 and 5 cuts significantly the magnitude of the estimated coefficients which nonetheless remain strongly significant. When controlling for both observable and unobservable characteristics of the firms in column 6, we find that the coefficient for the short-term horizon becomes larger in magnitude compared to the medium and long-term horizons, suggesting that the level of emissions has a larger impact on the short-term with respect to the long-term credit risk. In a sense, even if emission levels capture the long-term path towards net-zero emissions (Bolton and Kacperczyk, 2021*c*), a yearly decrease in carbon emissions reflects a short-term effort of the firms in decreasing their transition risk. The stronger effect that we observe for the short-term horizon supports the idea that measures

Table 2. Baseline Result using Emission Levels

Panel A						
Dep. Var.:	**1Y - EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-0.0354***	-0.0452***	-0.116***	-0.0261**	-0.0235*	-0.146***
	(0.00716)	(0.00834)	(0.0286)	(0.0130)	(0.0136)	(0.0293)
R-Squared	0.0736	0.0842	0.359	0.126	0.141	0.387
Panel B						
Dep. Var.:	**5Y - EDF**					
log(Scope 1)	-0.0751***	-0.0907***	-0.116***	-0.0338***	-0.0272**	-0.0915***
	(0.00701)	(0.00844)	(0.0199)	(0.0116)	(0.0123)	(0.0184)
R-Squared	0.0602	0.0918	0.617	0.151	0.190	0.647
Panel C						
Dep. Var.:	**10Y - EDF**					
log(Scope 1)	-0.127***	-0.146***	-0.134***	-0.0586***	-0.0462***	-0.0875***
	(0.00672)	(0.00815)	(0.0170)	(0.0104)	(0.0111)	(0.0149)
R-Squared	0.134	0.175	0.741	0.246	0.293	0.766
Firm-level controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	N	Y	Y	N
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	243718	243718	243718	233566	233566	233566

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample spans the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

of current climate risk, as proxied by backward-looking variables (i.e. carbon emissions), are relevant in showing the effect of climate risk on today's probability of default. However, once we shift the focus to longer-term horizons, forward-looking variables such as future emission targets or other measures of transition risk and physical risk could be more suitable for the analysis.

Results in Table 2 could be hard to digest if one has the prior that emissions are positively correlated with credit risk. Therefore, in the rest of Section 4.1 we break the analysis into smaller pieces in order to identify potential heterogeneous effects across firms with different levels of carbon emissions. Indeed, we repeat the baseline analysis on subgroups of firms divided by quintiles of carbon emissions.

Table 3 reports the estimated coefficients for the first and fifth quintiles of firms' emissions with year, country and industry fixed effects in Panel A and with year and firm fixed effects in Panel B. Panel A shows a negative (positive) effect on medium and long term EDF for firms with few (large) emissions. In other words, when looking within industries, firms that emit more are penalized in terms of EDF for any further increase in emissions, while small emitters tend to be safer. This finding is in line with previous studies. However, when introducing firms' fixed effects, the signs revert back to negative. Table 3 confirms that, in line with the previous studies, large emitters are penalized within industries, but overall we do not find that firms increasing their emissions bear higher credit risk. Instead, we do find that small emitters are not affected by an increase in Scope 1 emissions.[9]

To validate our baseline results, in the next section we check whether the coefficients estimated were not purely driven by the choice of our dependent variable by re-estimating our baseline equation using different measures of firms' creditworthiness such as Mean CDS Spread, Moody's Ratings and CDS implicit ratings.

[9]For a complete version of the table with all quintiles reported see Table A3 in the Appendix.

Table 3. Baseline Result using Emission Levels by Quintiles of emissions

Panel A **Dep. Var.:**	**1-Year EDF**		**5-Year EDF**		**10-Year EDF**	
Emissions' Quintile	1st	5th	1st	5th	1st	5th
log(Scope 1)	-0.0751	0.0570	-0.137***	0.0674**	-0.209***	0.0498**
	(0.0544)	(0.0382)	(0.0476)	(0.0315)	(0.0450)	(0.0251)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.183	0.153	0.224	0.253	0.297	0.322
N	48981	36521	48981	36521	48981	36521

Panel B **Dep. Var.:**	**1-Year EDF**		**5-Year EDF**		**10-Year EDF**	
Emissions' Quintile	1st	5th	1st	5th	1st	5th
log(Scope 1)	-0.0429	-0.380***	-0.0384	-0.175***	-0.0910**	-0.114**
	(0.0781)	(0.112)	(0.0545)	(0.0644)	(0.0441)	(0.0455)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.453	0.430	0.690	0.674	0.773	0.775
N	48980	36521	48980	36521	48980	36521

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample spans the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

4.2. Other Measures of Credit Risk

For comparability with previous studies, we use both absolute and relative firms' emissions to proxy for firms' transition risk. First, we analyze the correlations among the selected credit risk variables. Table 4 reports the pairwise correlation across 1, 5 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 are strongly correlated with short, medium and long-term EDF. Moody's and CDS implied ratings are highly correlated with 10-year EDF (0.63 and 0.77), but they display approximately half of the correlation coefficient with the 1-year EDF.

Table 4. 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	0.598*	1				
(3) CDS implied ratings	0.630*	0.773*	1			
(4) Y1-EDF	0.718*	0.389*	0.377*	1		
(5) Y5-EDF	0.708*	0.566*	0.546*	0.842*	1	
(6) Y10-EDF	0.666*	0.634*	0.598*	0.682*	0.945*	1

Note: The * indicate a 1% statistical significance.

Table 5 replicates our baseline specification with year, country and industry fixed effects in Panel A and year and firm fixed effects in Panel B. Panel A of Table 5 shows that higher emissions both in relative and level terms are associated with higher credit risks. The relationship is weaker for relative emissions as in Carbone et al., 2021. Notice that Moody's Ratings and CDS implied ratings are encoded in such a way that lower values indicate better credit scores. This result is in line with previous studies that document a positive relation between carbon emissions and credit risks (Capasso et al., 2020; Kabir et al., 2021; Carbone et al., 2021; Blasberg et al., 2021). Including firm fixed effect (column 3 of Panel B) we find that higher carbon emissions are correlated with better Moody's ratings. On the opposite, column 6 documents that higher carbon intensity leads to worse CDS implied ratings. All the other estimated coefficients are non-statistically significant. We interpret the results in this table as an indication that the relationship between climate risk (as proxied by emissions) and credit risk is positive only in certain special cases. In particular, the relation is positive only when looking at the effect within industry. Nevertheless, in the general case (effect across industries) we observe a robust negative relationship. For a detailed discussion on concerns and limitation see Section 4.7.

Table 5. Result - Other measures of credit risk

Panel A						
Dep. Var.:	**Mean CDS**		**Moody's Ratings**		**CDS implied Ratings**	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	9.523		0.100*		0.174*	
	(5.807)		(0.0533)		(0.0944)	
Carbon Intensity		0.0285**		0.000394***		0.000750***
		(0.0126)		(0.000125)		(0.000223)
Year, Country & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34582	34582	90000	90000	44403	44403
R-Squared	0.236	0.239	0.530	0.533	0.344	0.356
Panel B						
Dep. Var.:	**Mean CDS**		**Moody's Ratings**		**CDS implied Ratings**	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-12.57		-0.170***		-0.0488	
	(14.61)		(0.0503)		(0.125)	
Carbon Intensity		0.0187		0.000139		0.000892***
		(0.0201)		(0.000111)		(0.000255)
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34582	34582	89999	89999	44403	44403
R-Squared	0.551	0.550	0.930	0.929	0.793	0.795

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio, Asset Volatility and Capital Intensity. The dependent and independent variables are trimmed at the bottom and top 1%. The sample spans the years from 2008 to 2019. Standard errors in parentheses are are clustered at the Industry-Country-Year level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

The results reported in Table 5 corroborate the findings of the baseline analysis. Therefore, in order to investigate deeper the relationship between emissions and credit risk, in the next section we break down the EDF into its main components and analyze the effect of carbon emission on each one of them, trying to uncover the drivers of this apparently counter-intuitive result.

4.3. Decomposing EDF

EDFs measure the probability that a firm will default in the relative period of interest. There are three main components of a firm EDF: asset volatility, market value of assets and default point. Asset volatility defines the riskiness of a firm's assets as measured by the expected variation of the value of these assets over a given time horizon. The variable is calculated as the standard deviation of the annual percentage change in the market value of the firm's assets. Market value of assets is calculated by Moody's proprietary option-theoretic model and represents the current market value of a firm. The default point is the level of the firm's obligations, i.e. the level of the market value of a company's assets below which the firm would fail to make scheduled debt payments. In addition, we also include market leverage that is market value of assets divided by the default point.[10]

Before analyzing separately the effect of carbon emission on each component, we aim to understand how these components enter linearly in the EDF by running a simple OLS regression. This is a simplification compared to the actual mathematical function underlying the composition of EDF. Nonetheless, it will allow us to describe the relationship between carbon emissions and the probability of default through these mediator variables. Therefore, we establish a linear mapping of the EDF components to the EDF itself by estimating the following regression:

[10] See https://www.moodysanalytics.com/-/media/products/EDF-Expected-Default-Frequency-Overview.pdf

$$EDF_{it} = \alpha + \beta_1 * \text{Asset Vol.}_{it} + \beta_2 * \text{Market Value}_{it} + \beta_3 * \text{Default point}_{it} + \beta_4 * \text{Market Leverage}_{it} + \epsilon_{it} \tag{2}$$

Table 6 reports the estimated coefficients. We interpret these betas as the weights assigned to each variable in relation to the EDF. In columns 1 to 4, we include each component separately. As expected all of the coefficients are strongly significant. We notice that asset volatility and market leverage are associated with higher EDF, whereas higher default points and market value of assets are linked to lower default risks. When including all three key components (asset volatility, market value of assets and default point) in column 5 we notice that the default point changes sign. This is not surprising since default points depend on the firm's asset value and leverage. Indeed, in column 6 we run a check on the previous claim by including market leverage as well. We observe that both asset's market value and default point do switch sign, indicating the close relationship between the two. The results are robust to different horizons of EDF (see Table A4 in the Appendix).

We then exploit the sign of the estimated coefficients for the EDF components to understand what are the channels through which carbon emissions affect the EDF. Table 7 shows that higher Scope 1 is negatively correlated with asset volatility (column 1), market value (column 2) and default point (column 4), but positively correlated with market leverage (column 3). Thus suggesting that higher emissions lead to less volatile assets and lower market price, but also to larger firm leverage when looking at cross-firm variation within the same industry. In columns 5 to 8 we include firm fixed-effects. We find a negative effect on market leverage (column 7) and default point (column 8), but we do not find any statistical effect on market value (column 6).

Looking at the combined results from tables 6 and 7 we obtain a more clear-cut picture of the determinants that drive the relationship between carbon emissions and credit risk. Indeed, in Table 7 columns 1 and 5 show that carbon emissions affect negatively asset

Table 6. The weights of EDF's Components

Dep. Var.:	**1Y - EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Vol.	0.0273***				0.0269***	0.0857***
	(0.00205)				(0.00214)	(0.00290)
Market Value		-0.00000286***			-0.00000463***	0.00000642***
		(0.000000423)			(0.000000956)	(0.00000118)
Market Leverage			0.0463***			0.0754***
			(0.00214)			(0.00250)
Default Point				-0.00000445***	0.0000116***	-0.0000209***
				(0.00000136)	(0.00000283)	(0.00000425)
Constant	-0.0123	0.681***	-0.659***	0.652***	0.0214	-3.493***
	(0.0461)	(0.0248)	(0.0466)	(0.0240)	(0.0519)	(0.123)
N	243886	243886	243886	243886	243886	243886
R^2	0.029	0.007	0.218	0.002	0.035	0.437

Note: The dependent variable is 1-Year EDF. The table reports the estimated betas of using each EDF component separately from column 1 to 4, and then the three key components in column 5 plus market leverage in column 6. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table 7. What are the drivers?

	(1) Asset Volatility	(2) Market Value of Assets	(3) Market Leverage	(4) Default Point	(5) Asset Volatility	(6) Market Value of Assets	(7) Market Leverage	(8) Default Point
log(Scope 1)	-0.917***	-1878.9***	1.324***	-201.3	-0.423***	-142.1	-0.359**	-206.4**
	(0.0813)	(651.7)	(0.171)	(150.5)	(0.104)	(459.0)	(0.178)	(82.87)
Firm-level controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	N	N	N	N
Industry FE	Y	Y	Y	Y	N	N	N	N
Firm FE	N	N	N	N	Y	Y	Y	Y
N	233566	233566	233566	233566	233566	233566	233566	233566
R-Squared	0.618	0.336	0.388	0.286	0.911	0.864	0.820	0.916

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The Fixed Effects (FE) included are Year, Industry, Country and Firm FE. The independent variables are trimmed at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

volatility which in turn commands a lower probability of default (in column 5 of Table 6).[11] At the same time, in columns 2 and 6 the coefficients suggest that the higher carbon emissions either determine an increase in the probability of default through the channel of the market value of assets or they have no effect once the unobservable firm-level fixed components are taken into account. Finally, columns 4 and 8 show that when firm-level fixed effects are included, carbon emissions command a negative effect on the EDF through the default point channel.

Against this background, we can now stress the importance of factoring out all the sources of exogenous variation which are not directly related to the variable of interest and that could bias the estimates if not taken into account. In particular, it is now clear through which channel the introduction of firm-level fixed effects determines a negative coefficient in the estimated baseline equation. On the other hand, it is also evident how by absorbing only common cross-firm variation through industry fixed effects the magnitude of the coefficient in the baseline regression is largely reduced through the market value of assets channel.

In this section, we attempt to disentangle the effect of Scope 1 on firms' probability of default through the effect of emissions on each component of the EDF. Nevertheless, the analysis up to this point was conducted using the whole time span available assuming the relationship remained stable for the whole period considered. The easiest objection is that this assumption is too strong and the actual relationship has changed over time, given the growing interest that climate change has attracted in the last five to ten years. Therefore, we identified the 2015 Paris Climate Accords as a time of the structural break in climate change-related policies, which probably reverberated on firms' credit risk through its effect on transition risk.[12] To test this hypothesis, in the next section we split the sample into two

[11]We will use column 5 of Table 6 as a reference for the rest of the paragraph since it includes the three key components of the EDF

[12]Another possible structural break is the signature of the Principles for Responsible Investment (PRI) statement in 2016. When credit rating agencies as S&P and Moody's vowed to incorporate credit risks in their credit assessment. See Section 4.7 for a discussion of this.

sub-samples around the Paris Agreement date and replicate the baseline analysis.

4.4. Before and After Paris Agreement

The 2015 Paris Agreement constitutes a turning point in the collective awareness of the threats posed by climate risks. We, therefore, investigate whether the effect of emissions on companies' credit risk diverges in the years around the Paris agreement. As documented in Section 3, we observe that the 1-year EDF of the top quintiles converges to the EDF of the bottom quintiles after 2015. We corroborate this result by repeating our baseline regression on the two sub-samples: four years before and after the Paris Agreement. We then explore the channels driving the observed 2015 structural break. In order to investigate how EDFs and EDFs components are affected by an increase in transition risk, in keeping with Acharya et al. (2022), we estimate the following regression equation:

$$\mathrm{EDF}_{i,t} = \gamma_i + \gamma_t + \sum_{y=2009}^{2019} I_y[\beta_y Log(Scope1)_{i,t} + \theta_y Rating_{i,t}] + \beta Log(Scope1)_{i,t} + \theta Rating_{i,t} + \theta X_{i,t} + \epsilon_{it} \tag{3}$$

Where the dependent variable is either EDF (1-Year, 5-Year, and 10-Year EDF) or EDF components (asset volatility, market value of assets and default point) for firm i at time t. I_y are year indicators. The coefficient of interest β_y is the year-by-year sensitivity of EDF to absolute emissions relative to the base year 2008. To compare firms with similar credit ratings within the same year, we include Moody's credit ratings interacted with the year indicators. Control variables in $X_{i,t}$ are size, debt ratio, operating margin ratio, and capital intensity. We include firm and year fixed-effects and cluster standard errors at the firm level.

The first three columns of Table 8 report the estimated coefficients for the three main dependent variables (1, 5, and 10-year EDF). No statistically significant effect is observed before 2015. After 2015, the interaction between the year indicators and absolute emissions is positive and statistically significant. This suggests that relative to the base year of 2008, firms with higher absolute emissions, within the same credit rating score, bear higher credit

Table 8. Pre and Post Paris Agreement

Sample	Full Sample			1st Quintile Emission			5th Quintile Emission		
	(1) Y1-EDF	(2) Y5-EDF	(3) Y10-EDF	(4) Asset Vol.	(5) Market Val.	(6) Default Point	(7) Asset Vol.	(8) Market Val.	(9) Default Point
Log(Scope 1)	-0.130**	-0.0843**	-0.0646**	-0.523	-1487.3	-254.8	-0.657**	4150.8	-2628.7**
	(0.0572)	(0.0366)	(0.0260)	(1.516)	(1113.5)	(170.1)	(0.281)	(4222.5)	(1238.9)
I.2009*Log(Scope 1)	-0.0441	-0.0157	-0.00840	1.990*	-668.4	-101.3	-0.0906	-880.5	402.9
	(0.0280)	(0.00990)	(0.00612)	(1.142)	(549.6)	(104.3)	(0.0732)	(850.2)	(288.3)
I.2010*Log(Scope 1)	-0.00878	-0.0113	-0.0122	1.795	125.0	42.23	-0.0189	-1555.4	695.9
	(0.0292)	(0.0119)	(0.00792)	(1.209)	(694.0)	(77.66)	(0.103)	(975.3)	(457.9)
I.2011*Log(Scope 1)	0.00551	-0.00803	-0.0108	1.278	944.7	166.4	0.129	-1267.7	1042.0**
	(0.0342)	(0.0148)	(0.00984)	(1.305)	(833.3)	(104.8)	(0.121)	(1009.5)	(520.0)
I.2012*Log(Scope 1)	0.0179	-0.000438	-0.00638	0.308	1298.2	224.3*	0.160	-1076.3	1315.5**
	(0.0347)	(0.0159)	(0.0106)	(1.483)	(891.2)	(119.2)	(0.137)	(1314.3)	(627.8)
I.2013*Log(Scope 1)	0.0294	0.00902	-0.000721	0.472	1311.4	285.4**	0.239	195.1	1729.9**
	(0.0377)	(0.0174)	(0.0117)	(1.740)	(937.9)	(143.2)	(0.150)	(1793.2)	(742.8)
I.2014*Log(Scope 1)	0.0169	0.00764	0.000843	-1.026	1677.6*	291.1	0.269	-416.3	1505.0*
	(0.0386)	(0.0185)	(0.0128)	(1.773)	(918.6)	(191.3)	(0.165)	(1642.0)	(769.3)
I.2015*Log(Scope 1)	0.0561	0.0394*	0.0260*	-0.963	186.5	58.16	0.454**	-1829.0	1772.1**
	(0.0398)	(0.0203)	(0.0142)	(1.914)	(1106.7)	(222.1)	(0.181)	(1747.7)	(877.9)
I.2016*Log(Scope 1)	0.0912**	0.0612***	0.0419***	-2.267	-854.4	2.570	0.538***	-2163.0	1933.2*
	(0.0411)	(0.0209)	(0.0143)	(1.638)	(1674.5)	(231.2)	(0.197)	(1935.8)	(1051.3)
I.2017*Log(Scope 1)	0.0761*	0.0677***	0.0500***	-1.574	3266.3**	262.8	0.480**	-1594.2	2307.4**
	(0.0408)	(0.0213)	(0.0149)	(1.465)	(1580.0)	(228.2)	(0.195)	(2201.1)	(1161.3)
I.2018*Log(Scope 1)	0.0528	0.0524**	0.0403***	-1.359	4523.6**	431.2**	0.433**	-1401.2	1910.0*
	(0.0406)	(0.0209)	(0.0148)	(1.442)	(2083.9)	(215.8)	(0.181)	(2339.1)	(1030.4)
I.2019*Log(Scope 1)	0.0621	0.0464**	0.0341**	-0.940	3956.9*	652.4**	0.242	-663.8	2286.9*
	(0.0433)	(0.0226)	(0.0157)	(1.577)	(2034.2)	(273.6)	(0.167)	(3055.8)	(1353.6)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	89999	89999	89999	4276	4276	4276	33877	33877	33877
R^2	0.539	0.751	0.832	0.875	0.939	0.935	0.907	0.932	0.933

Note: The dependent variables for columns 1 to 6 are respectively 1-Year EDF,5-Year EDF, 10-Year EDF, Asset Volatility, Market Value of Assets, and Default point. We report in the table the coefficient for Log(Scope 1) and 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 Ratio, and Capital Intensity. The Fixed Effects (FE) included are Year and Firm. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

risk compared to firms with lower emissions. In the Appendix, we show the result of running our baseline regression on two sub-samples: years before and after the 2015 Paris agreement, using a 4-year window period (2011-2014 and 2016-2019). We find that in the four years preceding the Paris Agreement, an increase in direct emissions leads to a decrease in the medium and long-term probability of default. The estimated coefficients are similar in magnitude to those in the full specification of Table 2, with a larger effect on short-term credit risk. After the Paris Agreement, the estimated coefficients are not statistically different from zero. This is consistent with the results of Table 8.

Columns 4 to 9 of Table 8 report the estimated coefficients of the EDF components for firms in the 1st and 5th quintile of emissions. The results in the table indicate that small emitters experience an increase in the market value of assets associated to an increase in carbon emissions in 2014, 2017, 2018, and 2019. No effect is found for asset volatility while default point becomes significant only in the last two years of the sample. According to the signs estimated in Table 6 this translates in a net negative effect on EDF. Conversely, large emitters show a consistent positive sign for asset volatility since 2015 and a constant increase in the default point coefficient; thus, a net positive effect on EDF. Overall, these results indicate that the observed convergence in credit risk between small and large emitters is mostly driven by a change in asset volatility. Regarding Table 8, the reader may have noticed the difference in sizes between the 1st and 5th quintile sub-sample. This imbalance is due to the absence of a rating for a significant number of firms belonging to the bottom quintile. While using firms' ratings is necessary to keep with the specification introduced in Acharya et al. (2022), we believe that the imbalance between the two sub-samples is not crucial for the results. Indeed, in the Appendix (Table A7) we show that the convergence of small and large emitters' probabilities of default is confirmed also with more balanced samples. Nonetheless, this latter results might again raise the doubt that with this econometric specification we are capturing a size effects rather than the effect of emissions. However, we discuss and then rule out this possibility in Section 4.7. [13]

In the next section, we will focus on several firms' characteristics to show how firms' heterogeneity reshapes the relationship between carbon emissions and credit risk. The exercise will also allow us to uncover some relevant characteristics that could affect credit risk and be relevant from a policy perspective that would not be visible by looking at the entire sample.

4.5. Geographic Area

In this section, we explore whether the geographical location of a firm is relevant when studying the relationship between climate and credit risk. Previous studies as Seltzer et al. (2022) document that the effect of transition risk on credit risk is higher in jurisdictions with more stringent regulations. Accordingly, Carbone et al. (2021) show that EU firms have experienced a worsening in ratings after the Paris Agreement compared to US firms. They also show that, in the US, credit ratings improved for the top polluters after 2015. Bolton and Kacperczyk (2021*c*) instead, find that short-term transition risk is greater for firms located in countries with lower economic development. While long-term transition risk is higher in countries with stricter domestic, but not international, climate policies.

Table 9 reports the estimated coefficients for the US, Euro Area, and Great Britain, respectively in columns 1 to 3 and columns 4 to 6. All columns include firm-level controls. Columns 1 to 3 have industry and time-fixed effects and columns 4 to 6 add firm-level fixed effects. For the Euro Area, we also include country-fixed effects to control for individual countries' characteristics.

Columns 1 and 4 document a negative and statistically significant effect for firms located in the United States for both specifications with industry and firm fixed effects. Interestingly,

[13] In the Appendix, we show that our results are robust to different specifications. We run the following regression on the 4-year windows before and after 2015 (2011-2014 and 2016-2019): $\text{EDF Component}_{it} = \alpha + \beta_1 1(\text{Post 2015})_t + \beta_2 \text{Log}(\text{Scope 1})_{it} + \beta_3 1(\text{Post 2015})_t \text{Log}(\text{Scope 1})_{it} + \beta_4 X_{it} + \gamma_i + \epsilon_{it}$. Table A7 reports the result for all sample (column 1-3), firms in the 1st quintile of emissions (column 4-6), and firms in the 5th quintiles (column 7-9). The estimated coefficients corroborate the results of Table 8. Additionally, Table A8 reports the results for all quintiles of emissions.

Table 9. Results by Geographical Location

Panel A						
Dep. Var.:	**1Y - EDF**					
	(1) US	(2) EU	(3) GB	(4) US	(5) EU	(6) GB
log(Scope 1)	-0.0705***	0.0342*	0.0493	-0.162***	-0.103*	0.00959
	(0.0195)	(0.0176)	(0.0304)	(0.0341)	(0.0576)	(0.0802)
R-Squared	0.167	0.141	0.126	0.400	0.389	0.356
Panel B						
Dep. Var.:	**5Y - EDF**					
log(Scope 1)	-0.0746***	0.0315*	0.0473	-0.102***	-0.0594**	0.00748
	(0.0172)	(0.0168)	(0.0309)	(0.0219)	(0.0285)	(0.0707)
R-Squared	0.234	0.177	0.210	0.667	0.606	0.610
Panel C						
Dep. Var.:	**10Y - EDF**					
log(Scope 1)	-0.0904***	0.0148	0.00695	-0.0972***	-0.0458**	-0.0185
	(0.0157)	(0.0142)	(0.0263)	(0.0177)	(0.0210)	(0.0530)
R-Squared	0.336	0.278	0.359	0.783	0.724	0.746
Year FE	Y	Y	Y	Y	Y	Y
Country FE	N	Y	N	N	N	N
Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
N	157352	52854	23360	157352	52854	23360

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

column 2 shows that in the Euro Area the estimated coefficient is positive and statistically significant for 1-year and 5-year EDF, implying that firms with higher emissions within the same industry have higher credit risk. This coefficient shifts to negative for all three EDF's horizons, once we include the fixed effects. The estimated coefficients for the EU are lower in magnitude compared to the US, but they still show a stronger effect for short-term credit risk. Nonetheless, the R-Squared becomes approximately three times higher from columns 1 to 3 to columns 4 to 6, once again corroborating the importance of adding controls for firms' unobservables.

4.6. Forward Looking Transition Risk

Different specifications of carbon emissions indicate different types of transition risks. Our analysis was conducted using emission levels, i.e. the long-term effect of carbon emissions. Since absolute emission is backward-looking, it may be possible that the EDF is better at capturing the forward-looking emission effect. Thus, we replicate the analysis using carbon earnings-at-risks from Trucost.[14] 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 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 2019. We choose the 2030 earnings-at-risk horizon because it allows us to exploit the 10-year long-term EDF to investigate whether EDF includes forward-looking risks. We hypothesize, given the sample years included (i.e. 2017 to 2019) and since we observe a switch in behavior after 2015, that carbon earnings at risk should be reflected in EDFs.

Table 10 shows that EDF is positively correlated to the effect of forward-looking transition

[14] In the next section we use for robustness the rate of change of carbon emission (i.e. the short-term effect), relative emissions (carbon intensity), and the temporal effect of emissions (lagged values).

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

Table 10. Forward Looking Transition Risk

Dep. Var.:	**10Y - EDF**								
Emission Quintiles	All			1st Quintile			5th Quintile		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1)	-0.0308**	-0.0400***	-0.0370***	-0.0862*	-0.0866*	-0.0863*	-0.0797**	-0.106***	-0.101***
	(0.0120)	(0.0125)	(0.0125)	(0.0471)	(0.0469)	(0.0469)	(0.0366)	(0.0381)	(0.0383)
FLR Low	0.00724**			0.0274			0.00932***		
	(0.00283)			(0.0267)			(0.00338)		
FLR Medium		0.00495***			0.0167			0.00574***	
		(0.00146)			(0.0148)			(0.00175)	
FLR High			0.00246***			0.00840			0.00303***
			(0.000801)			(0.00772)			(0.000954)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.906	0.906	0.906	0.262	0.264	0.263	0.426	0.440	0.434
N	51849	51849	51849	8473	8473	8473	11291	11291	11291

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio, and Capital Intensity. The sample span the years from 2017 to 2019. FRL stands for Forward-Looking Risk calculated as 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). For the analysis, we use the firm's carbon earnings at risk as a percentage of EBITDA for both Low, Medium, and High policy scenarios in 2030. The log(Scope 1) and 10-Year EDF variables were winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

risks (FLR) for both low, medium, and high policy scenarios. The first three columns use the whole samples of firms and they add each FLR separately. We notice that Scope 1 emissions are still significant, but the effect is somehow mitigated. When we separate small and large emitters, we find that the effect is driven by firms with high emissions. In the Appendix, we report Table A10 which includes also the firm-fixed effect. According to A10 the effect is null at the quintiles level. However, we argue that this effect may be driven by the small sample in terms of firms and years.

4.7. Concerns and Limitations

In this final section, we want to be transparent about some concerns and limitations of our analysis.

Sample selection. We acknowledge that our sample may suffer from selection bias. The selected sample comprehends all firms with MSCI carbon emissions from the US, UK, Japan and Euro Area that we could match with Moody's EDFs. In terms of market capitalization, our dataset covers approximately 60% of the US equity market and 34% and 22% of the UK and EMU markets.[16] While we are aware of the small coverage, we believe that this is already a large improvement of coverage compared to the sample coverage of other instruments such as CDS. In our sample, CDS covers approximately 33%, 26%, and 13% of the US, UK, and EMU markets. However, we have to acknowledge that if our sample is somehow biased towards firms that are not penalized by high emissions, this could explain why we find a negative correlation between transition and credit risk.

Emission data providers. There are data challenges in estimating firms' carbon emissions Papadopoulos (2021). Thus, different providers of carbon emissions data are not fully comparable. To address this concern, we collect direct emission data from Trucost, Refinitiv and Carbon4. First, we find that MSCI Scope 1 emissions are highly correlated with all providers, respectively 0.93, 0.97 and 0.9 for Carbon4, Refinitiv and Trucost. Thus, reassuring us that our dependent variable is highly correlated to other emission variables. Second, we look at the firms' coverage of our sample compared to other providers' coverage. Table 11 shows the number of firms in our sample that we could match with the emission level data from the other providers. Refinitiv and Trucost have emission data for approximately half of our sample, while Carbon4 data matches 20% of the firms in our sample, but overall matches

[16] Market cap is the market capitalization of listed domestic companies (current US$) from the World Bank data.

only 2% of our panel. This is because no data is available before 2014 and most of the data come from 2019.

Additionally, we notice that the matched sample (with other carbon data providers) covers firms with overall lower credit risks, greater size, larger leverage, and operating margin. In the Appendix, we also re-run the baseline analysis using the collected emissions variables for firms in our samples and in the matched sample (Carbon4, Refinitiv, and Trucost). When using the matched sample, we do not find any statistically significant effect of emission on EDF. We believe this is because our sample is able to capture smaller firms, which indeed seem to be a relevant driver of the negative coefficient on carbon emissions.

Table 11. Firms coverage of different providers of carbon emissions

Data	All Sample (MSCI)	Carbon4	Refinitiv/ESG	Trucost
	243,889	5,325	79,815	82,786
Unique firms	1841	360	1034	864
% all sample (panel)		2%	33%	34%
% all sample (firms)		20%	56%	47%

Size and productivity channel. A concern is that what we are capturing is a size or productivity effect. Firms that are larger, produce and emit more, thus having lower credit risk. While we control for size in our regressions and we add firm fixed effects to mitigate the effect of firms' fixed characteristics, we are aware that this may not fully capture a possible size or productivity channel. We then report the results of a regression using different proxies of the firm's size such as working capital, long-term tangible assets (property, plant and equipment), and intangible assets. Table 12 report the estimated coefficients, first for the baseline regression, then by adding one variable at a time. We notice that our independent variable of interest (carbon emissions) remains statistically significant in all specifications and with similar magnitude. In the Appendix, Table A9 reports the baseline results separately for firm size's quintile. We observe that the results are driven by small as well as large firms.

Thus reassuring us that the observed effect is not purely driven by small firms.

Table 12. Controlling for firms' size

	1-Year EDF				5-Year EDF				10-Year EDF			
	baseline	(1)	(2)	(3)	baseline	(1)	(2)	(3)	baseline	(1)	(2)	(3)
Log(Scope 1)	-0.166***	-0.175***	-0.173***	-0.183***	-0.105***	-0.112***	-0.110***	-0.114***	-0.101***	-0.105***	-0.104***	-0.104***
	(0.0352)	(0.0352)	(0.0355)	(0.0358)	(0.0225)	(0.0225)	(0.0226)	(0.0226)	(0.0182)	(0.0182)	(0.0182)	(0.0182)
Size	-0.0850	-0.101	-0.113	-0.0357	-0.254***	-0.266***	-0.274***	-0.246***	-0.320***	-0.329***	-0.338***	-0.333***
	(0.0804)	(0.0799)	(0.0799)	(0.0813)	(0.0509)	(0.0502)	(0.0503)	(0.0522)	(0.0378)	(0.0374)	(0.0375)	(0.0396)
Debt ratio	3.074***	2.869***	2.873***	2.895***	2.218***	2.070***	2.073***	2.081***	1.681***	1.569***	1.572***	1.574***
	(0.329)	(0.315)	(0.315)	(0.319)	(0.191)	(0.185)	(0.185)	(0.186)	(0.141)	(0.139)	(0.138)	(0.139)
Operating maring	37.00***	35.48***	35.23***	36.37***	23.43**	22.34**	22.15**	22.58**	14.97	14.14	13.94	14.02
	(11.51)	(10.38)	(10.35)	(9.792)	(10.75)	(9.962)	(9.949)	(9.725)	(10.28)	(9.725)	(9.715)	(9.666)
Capital Intensity	2.348***	1.839***	1.752***	1.055*	1.265***	0.898***	0.835***	0.576*	0.755***	0.477**	0.408**	0.357
	(0.470)	(0.476)	(0.483)	(0.568)	(0.267)	(0.269)	(0.274)	(0.315)	(0.197)	(0.199)	(0.203)	(0.235)
WC Ratio		-1.265***	-1.269***	-1.794***		-0.913***	-0.916***	-1.111***		-0.690***	-0.694***	-0.732***
		(0.273)	(0.273)	(0.399)		(0.158)	(0.158)	(0.211)		(0.121)	(0.121)	(0.158)
PPE			8.033*	7.601*			5.758**	5.598**			6.355***	6.324***
			(4.501)	(4.462)			(2.652)	(2.614)			(2.199)	(2.186)
Intangible asset ratio				-1.085***				-0.404*				-0.0794
				(0.391)				(0.221)				(0.169)
Constant	1.613**	2.289***	2.351***	2.391***	3.087***	3.575***	3.619***	3.634***	4.121***	4.490***	4.539***	4.542***
	(0.653)	(0.697)	(0.695)	(0.696)	(0.412)	(0.428)	(0.428)	(0.427)	(0.319)	(0.326)	(0.326)	(0.326)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	155073	155073	155073	155073	155073	155073	155073	155073	155073	155073	155073	155073

Note: The dependent and independent variables are winsorized at the bottom and top 1%. The sample spans the years from 2008 to 2019. Standard errors in parentheses are clustered at the firm level.
* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Change in investors' or Moody's climate awareness. The change in credit risk between large and small emitters after 2015 may be driven by an increase in climate awareness from the 2015 Paris Agreement as well as a change in Moody's methodology. In 2016, Moody's signed the Principles for Responsible Investment (PRI) which pledged to take into consideration climate-related aspects in its assessment. Albeit studies such as Kiesel and Lücke (2019) indicate that GHG emissions are taken into account in credit ratings, discrepancies between Moody's ratings and Moody's EDFs could suggest that the two measures capture different faces of default risk. Indeed, Table 5 indicates that an increase in emission leads to lower ratings, which is in contrast to what we find using EDF as the dependent variable. However, when including firm fixed effect, the baseline results obtained using credit ratings are aligned with the EDF results, supporting the evidence that credit ratings and EDF proxy similar default risks and the results seem to be driven by investors' sentiment.

4.8. Robustness

Transition risk. Our analysis was conducted using emission levels, i.e. the long-term effect of carbon emissions. We now replicate our baseline results using the rate of change of carbon emission (i.e. the short-term effect) in Table A11, relative emissions (carbon intensity) in Table A12, and the temporal effect of emissions (lagged values) in Table A13.

The first three columns of Table A11 show that once we switch the focus from the long-term to the short-term, we don't see any significant effects of Scope 1 emissions on EDF except for the 10-year horizon. While the coefficients in columns 1 and 2 are not statistically significant, in column 3 the relevant coefficient is strongly significant and positive. This result, in contrast with the negative coefficient of the baseline regression, indicates that a positive change in the rate of carbon emission today will not significantly affect the probability of default in the short term. Nonetheless, we observe a substantial effect on the default probability at longer horizons. Columns 4, 5, and 6 replicate the same analysis with the inclusion of firm fixed effects. In these columns the sign of the coefficients is consistent with the findings of the first three columns, but the effect is muted.

Table A12 replicates the baseline results using the carbon intensity as independent variable of interest. In this table the coefficients are not consistent across the different specifications and the effect is muted for most of the estimated coefficients. These findings corroborate our initial hypothesis that relative measures of carbon emission do not convey significant information when investigating the effect of carbon emissions on credit risk.

Finally, to test further the robustness of the measure of climate risk selected, in Table A13 we replicate the baseline specification replacing the Scope 1 emissions variable with its one-period and two-period lagged values. The sign of the estimated coefficients in all columns, for both panels, is consistent with those presented in Table 2, yet with lower significance.

Decomposition by ratings, sector and public ownership. In Table A14 we look also at Moody's credit ratings, the "greenness" of the industry of reference and the presence of a majority stake in the company's capital owned by a Government entity. We define "good rating" firms as firms with investment grade ratings (from Aaa to Baa3), while "bad rating" firms those with ratings below investment grade (Baa1 to Caa3). We notice that, for all rating classes, the direct emission explanatory variable is negative and statistically significant at the 1% level. However, good rating firms have an estimated coefficient almost 12 times larger than bad rating firms. The second specification in columns 3 and 4 of Table A14 is also interesting as it conveys information that was hidden in previous tables. Indeed, columns 3-4 show that for firms operating in brown industries high carbon emissions are related to a higher probability of default at the short and medium-term horizons. This effect is absent for firms belonging to greener industries. [17] The specification in columns 3-4 uses industry-fixed effects that absorb common cross-firm variation. Therefore, once factored out the effect of the industry, we observe a systematic difference between firms in the two categories. We interpret this as a signal that the inherent characteristics of firms belonging to different industries are relevant when analyzing the effect of climate on credit risks. In particular, in our view, columns 4 and 5 suggest that there might be a threshold of emission, although fuzzy, set implicitly by climate policies above which the carbon restrictions become more binding and thus a change in emissions is reflected on firms' credit risk. This interpretation becomes even more intuitive when thinking at the Emission Trading System which allows a certain amount of emissions for firms above which they should enter the market to purchase more polluting rights. On the contrary, when performing the same regression substituting industry

[17] Green industries are consumer discretionary, staples, healthcare and telecommunications; while brown industries are: utilities, energy industries and materials.

level with firm-level fixed-effects (columns 9-10) the effect mostly disappears also for firms in brown industries. In view of the explanation provided above, this outcome was expected as we postulated that the effect of carbon emissions is channeled to the probability of default through firm's inherent characteristics, which are partly "absorbed" in this specification. Finally, columns 5-6 and 11-12 show that the effect of carbon emission is strongly significant for firms characterized by low Government ownership. While we do not observe any effect on firms with high Government ownership. We interpret these coefficients as evidence that the probability of default of mostly Government-owned firms is driven by considerations other than climate risk. Although this explanation is uncontroversial, we notice that the sub-sample of publicly owned firms is relatively small compared to the other sub-sample.

Other Robustness. Table A15 include month-year FE instead of year FE. Table A16 and A17 exclude sectors such as Utilities and Manufacturing respectively, that are associated with high emission levels but low credit risks. Figure A2 fix quintiles of emission at the first year of the firm in our sample, in order to check that the results are not driven by time-varying effect. Table A18 estimates the baseline results using the whole sample, with all variables aggregated at the yearly level. We notice that the relationship of interest is robust across all specifications.

5. Conclusions

We use a comprehensive, yet parsimonious approach to estimate the effect of carbon emissions on credit risk. We show that carbon emissions are relevant for the probability of default by means of asset volatility. We also provide evidence that the 2015 Paris Agreement marked a policy turning point that reverberated on firms' credit risk. After 2015, our results suggest that firms with high carbon footprints became riskier. We observe that this relation is driven by a decrease (increase) in asset volatility of small (large) emitters. We interpret this as an indication that the gap between large and small emitters narrowed after the

Paris Agreement. Further, we document how firms' heterogeneity may affect the estimated relationship. We find that the relationship is stronger for large emitters, firms belonging to "brown" sectors, firms with low public ownership, and firms in the US.

In summary, using our methodology we are able to provide evidence on how firms' probability of default is affected by climate risk and through which component of the credit risk this effect is channeled. While this approach leaves us with little to say about the magnitude of the uncovered effects, we believe that this work opens up a new path for the research on the topic which focuses on the drivers of the probability of default and quantifying the effect of carbon emissions on credit risk possibly by means of an underlying structural model. While these extensions are interesting and worthy of future investigation, we believe that our work delivers novel and insightful implications despite the simplifying assumptions.

References

Acharya, V. V., Johnson, T., Sundaresan, S. and Tomunen, T. (2022), Is physical climate risk priced? evidence from regional variation in exposure to heat stress, Technical report, National Bureau of Economic Research.

Barth, F., Hübel, B. and Scholz, H. (2020), 'Esg and corporate credit spreads', *Available at SSRN 3179468* .

Berg, F., Kölbel, J. F. and Rigobon, R. (2020), 'Aggregate confusion: The divergence of esg ratings', *Available at SSRN 3438533* .

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

Bolton, P. and Kacperczyk, M. (2021*a*), Carbon disclosure and the cost of capital, Technical report, Available at SSRN 3755613.

Bolton, P. and Kacperczyk, M. (2021*b*), 'Do investors care about carbon risk?', *Journal of Financial Economics* .

Bolton, P. and Kacperczyk, M. (2021*c*), Global pricing of carbon-transition risk, Technical report, National Bureau of Economic Research.

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

Carbone, S., Giuzio, M., Kapadia, S., Krämer, J. S., Nyholm, K. and Vozian, K. (2021), 'The low-carbon transition, climate commitments and firm credit risk'.

Devalle, A., Fiandrino, S. and Cantino, V. (2017), 'The linkage between esg performance and credit ratings: a firm-level perspective analysis'.

Gao, F., Li, Y., Wang, X. and Zhong, Z. (2020), 'Corporate social responsibility and the term structure of cds spreads', *Available at SSRN 3356165* .

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

Guimaraes, P. and Portugal, P. (2010), 'A simple feasible procedure to fit models with high-dimensional fixed effects', *The Stata Journal* **10**(4), 628–649.

Henisz, W. J. and McGlinch, J. (2019), 'Esg, material credit events, and credit risk', *Journal of Applied Corporate Finance* **31**(2), 105–117.

Höck, A., Klein, C., Landau, A. and Zwergel, B. (2020), 'The effect of environmental sustainability on credit risk', *Journal of Asset Management* **21**(2), 85–93.

Ilhan, E., Sautner, Z. and Vilkov, G. (2021), 'Carbon tail risk', *The Review of Financial Studies* **34**(3), 1540–1571.

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

Kiesel, F. and Lücke, F. (2019), 'Esg in credit ratings and the impact on financial markets', *Financial Markets, Institutions & Instruments* **28**(3), 263–290.

Klusak, P., Agarwala, M., Burke, M., Kraemer, M. and Mohaddes, K. (2021), 'Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness'.

Kölbel, J. F., Leippold, M., Rillaerts, J. and Wang, Q. (2020), 'Ask bert: How regulatory disclosure of transition and physical climate risks affects the cds term structure', *Available at SSRN 3616324* .

Kotró, B. and Márkus, M. (2020), 'The impact of esg rating on corporate bond yields', *ECONOMY AND FINANCE: ENGLISH-LANGUAGE EDITION OF GAZDASÁG ÉS PÉNZÜGY* **7**(4), 474–488.

Merton, R. C. (1974), 'On the pricing of corporate debt: The risk structure of interest rates', *The Journal of finance* **29**(2), 449–470.

Papadopoulos, G. (2021), 'Data challenges in the corporate ghg emissions landscape', *4th Summer School on Sustainable Finance* .

Sautner, Z., van Lent, L., Vilkov, G. and Zhang, R. (2020), 'Firm-level climate change exposure'.

Seltzer, L. H., Starks, L. and Zhu, Q. (2022), Climate regulatory risk and corporate bonds, Technical report, National Bureau of Economic Research.

Stellner, C., Klein, C. and Zwergel, B. (2015), 'Corporate social responsibility and eurozone corporate bonds: The moderating role of country sustainability', *Journal of Banking & Finance* **59**, 538–549.

Zhang, B. Y., Zhou, H. and Zhu, H. (2009), 'Explaining credit default swap spreads with the equity volatility and jump risks of individual firms', *The Review of Financial Studies* **22**(12), 5099–5131.

Appendix

Table A1. 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
NAICS code	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
Market Leverage	Market Leverage (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
Book Value Equity	Common Equity	CRSP/Compustat
Research And Development	Quarterly Research & Development Expenses	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.

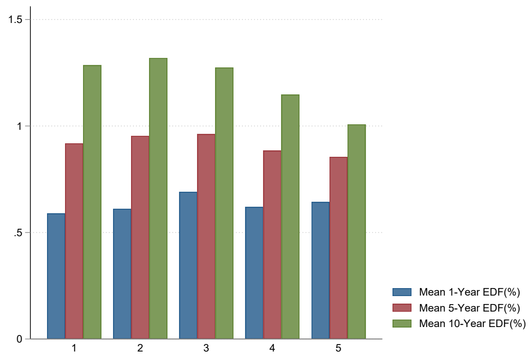
Table A2. Summary Statistics of firms characteristics between the 1st and 5th Quintile of Emission levels

1st Quintile	Mean	p50	SD	Min	Max	count
1 Year EDF	0.79	0.17	1.99	0.01	28.83	48854
5 Year EDF	1.29	0.76	1.45	0.06	11.36	48854
10 Year EDF	1.85	1.42	1.32	0.12	7.67	48854
Mean CDS Spreads	214.95	94.94	320.35	40.50	2885.58	568
Carbon Intensity	20.35	16.10	25.83	1.30	420.10	48854
Ln(scope 1)	6.41	6.65	1.12	3.22	8.19	48854
Size	6.31	6.21	1.46	0.62	15.54	48854
Debt Ratio	0.21	0.13	0.26	0.00	6.04	48809
Operating Margin Ratio	-18.25	0.29	621.38	-70046.99	6193.11	46519
Asset Volatility	33.36	31.10	14.55	2.45	96.75	48854
Market Value of Assets	3118.14	1193.07	6896.43	8.76	179764.59	48854
Market Leverage	19.95	13.90	18.43	0.04	99.99	48854
Default Point	626.88	157.78	1500.15	0.08	24505.56	48854
Moody's Ratings'	12.57	13.00	3.29	6.00	19.00	4440
Derived CDS Ratings	10.29	10.00	3.22	3.00	20.00	871
Capital Intensity	0.13	0.07	0.16	0.00	0.96	48752
Book Value Equity	501.87	252.89	858.92	-2410.86	12876.99	35460
Research And Development	0.04	0.03	0.06	0.00	1.13	27826
Intangible Assets	0.20	0.12	0.23	0.00	0.92	35460
Observations	48854					

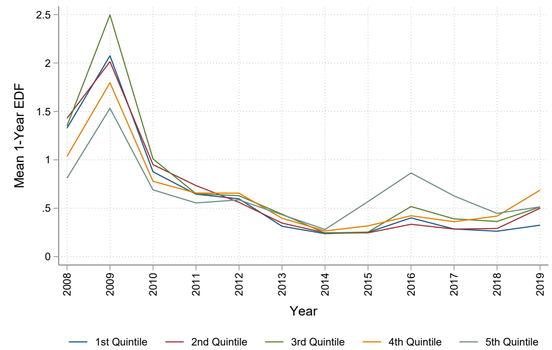
5th Quintile	Mean	p50	SD	Min	Max	count
1 Year EDF	0.48	0.06	1.40	0.01	28.83	48658
5 Year EDF	0.64	0.27	1.03	0.06	11.36	48658
10 Year EDF	0.76	0.45	0.87	0.12	7.67	48658
Mean CDS Spreads	128.87	74.64	188.96	15.64	2885.58	18542
Carbon Intensity	957.43	450.70	1288.60	2.10	5632.00	48659
Ln(scope 1)	14.85	14.61	1.43	12.81	18.04	48659
Size	9.51	9.48	1.40	5.08	13.65	48659
Debt Ratio	0.31	0.30	0.14	0.00	1.39	48659
Operating Margin Ratio	0.56	0.39	149.72	-15832.00	6708.00	47102
Asset Volatility	16.87	15.45	6.85	3.72	51.09	48658
Market Value of Assets	47922.50	17006.47	85848.21	194.44	1113578.00	48658
Market Leverage	35.45	34.07	16.22	0.60	98.38	48658
Default Point	15934.63	5296.05	33457.05	20.72	532462.94	48658
Moody's Ratings'	9.25	9.00	3.28	1.00	21.00	35163
Derived CDS Ratings	7.70	8.00	3.85	1.00	21.00	23329
Capital Intensity	0.46	0.45	0.22	0.00	0.97	48659
Book Value Equity	13080.11	4265.00	25276.11	-17577.00	198646.00	33526
Research And Development	0.01	0.00	0.01	-0.00	0.20	13036
Intangible Assets	0.16	0.09	0.18	0.00	1.10	33382
Observations	48659					

Note: 1-Year EDF, 5-Year EDF, 10-Year EDF, 5-Year CDS Spreads, Scope 1 Emission and Carbon Intensity are winsorized at the bottom and top 1%. See table A1 for variables' description and sources.

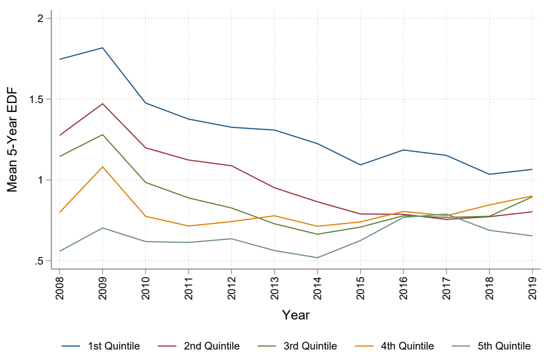
Figure A1. Mean EDF by quintiles



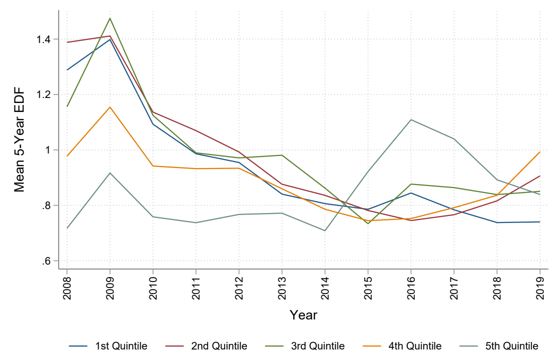
(a) Carbon Intensity



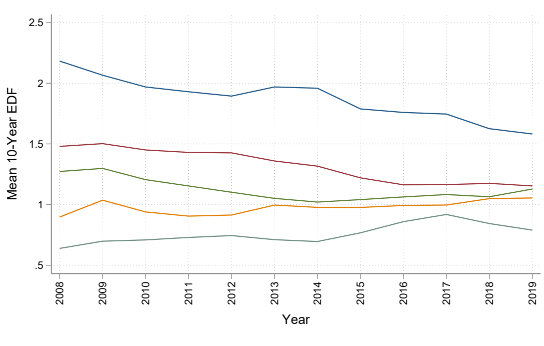
(b) Carbon Intensity & 1-Year EDF



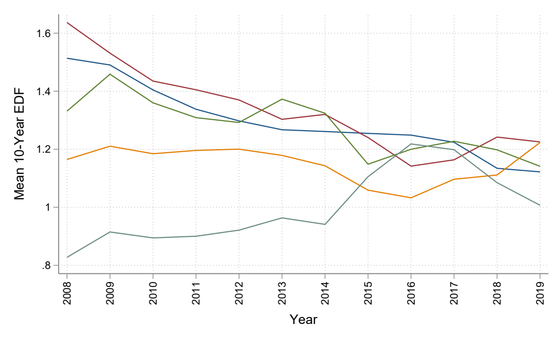
(c) ln(Scope 1) & 5-Year EDF



(d) Carbon Intensity & 5-Year EDF



(e) ln(Scope 1) & 10-Year EDF



(f) Carbon Intensity & 10-Year EDF

Table A3. Baseline Result using Emission Levels by Quintiles of emissions

Panel A	1-Year EDF					5-Year EDF					10-Year EDF				
Emissions' Quintile	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
log(Scope 1)	-0.0751	0.0649	0.0597	-0.107	0.0570	-0.137***	0.0443	0.0489	-0.0864	0.0674**	-0.209***	0.0491	0.00212	-0.0959**	0.0498**
	(0.0544)	(0.0813)	(0.0776)	(0.0745)	(0.0382)	(0.0476)	(0.0668)	(0.0651)	(0.0575)	(0.0315)	(0.0450)	(0.0585)	(0.0580)	(0.0483)	(0.0251)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.183	0.184	0.156	0.142	0.153	0.224	0.233	0.191	0.206	0.253	0.297	0.297	0.251	0.267	0.322
N	48981	49386	49386	48872	36521	48981	49386	49386	48872	36521	48981	49386	49386	48872	36521

Panel B	1-Year EDF					5-Year EDF					10-Year EDF				
Emissions' Quintile	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
log(Scope 1)	-0.0429	-0.0515	-0.364***	-0.304**	-0.380***	-0.0384	-0.117*	-0.230***	-0.160	-0.175***	-0.0910**	-0.128**	-0.207***	-0.127*	-0.114**
	(0.0781)	(0.112)	(0.125)	(0.151)	(0.112)	(0.0545)	(0.0650)	(0.0712)	(0.0997)	(0.0644)	(0.0441)	(0.0506)	(0.0522)	(0.0738)	(0.0455)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.453	0.476	0.465	0.429	0.430	0.690	0.714	0.713	0.661	0.674	0.773	0.801	0.804	0.755	0.775
N	48980	49386	49386	48871	36521	48980	49386	49386	48871	36521	48980	49386	49386	48871	36521

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample spans the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A4. Robustness EDF's Components

	(1)	(2)	(3)	(4)
	5-Year EDF	5-Year EDF	10-Year EDF	10-Year EDF
asset volatility	0.0340***	0.0810***	0.0441***	0.0814***
	(0.00202)	(0.00201)	(0.00185)	(0.00171)
market value of assets	-0.00000505***	0.00000379***	-0.00000536***	0.00000165***
	(0.000000966)	(0.000000725)	(0.000000996)	(0.000000459)
default point	0.0000113***	-0.0000148***	0.0000106***	-0.0000100***
	(0.00000235)	(0.00000323)	(0.00000216)	(0.00000272)
market leverage		0.0604***		0.0479***
		(0.00151)		(0.00113)
Cons	0.148***	-2.666***	0.211***	-2.021***
	(0.0493)	(0.0736)	(0.0456)	(0.0559)
N	243886	243886	243886	243886
R^2	0.113	0.642	0.226	0.635

Note: The dependent variables are 5-Year and 10-Year EDF. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$.

Table A5. Pre and Post Paris Agreement - with Market leverage

Sample	Full Sample			1st Quintile Emission				5th Quintile Emission			
	(1) Y1-EDF	(2) Y5-EDF	(3) Y10-EDF	(4) Asset Vol.	(5) Market Val.	(6) Market Lev.	(7) Default Point	(8) Asset Vol.	(9) Market Val.	(10) Marlet Lev.	(11) Default Point
Log(Scope 1)	-0.130**	-0.0843**	-0.0646**	-0.523	-1487.3	-1.601	-254.8	-0.657**	4150.8	-1.780**	-2628.7**
	(0.0572)	(0.0366)	(0.0260)	(1.516)	(1113.5)	(2.921)	(170.1)	(0.281)	(4222.5)	(0.701)	(1238.9)
I.2009*Log(Scope 1)	-0.0441	-0.0157	-0.00840	1.990*	-668.4	-2.602	-101.3	-0.0906	-880.5	0.338	402.9
	(0.0280)	(0.00990)	(0.00612)	(1.142)	(549.6)	(2.456)	(104.3)	(0.0732)	(850.2)	(0.228)	(288.3)
I.2010*Log(Scope 1)	-0.00878	-0.0113	-0.0122	1.795	125.0	-1.276	42.23	-0.0189	-1555.4	0.958***	695.9
	(0.0292)	(0.0119)	(0.00792)	(1.209)	(694.0)	(2.015)	(77.66)	(0.103)	(975.3)	(0.317)	(457.9)
I.2011*Log(Scope 1)	0.00551	-0.00803	-0.0108	1.278	944.7	-1.060	166.4	0.129	-1267.7	1.107***	1042.0**
	(0.0342)	(0.0148)	(0.00984)	(1.305)	(833.3)	(2.851)	(104.8)	(0.121)	(1009.5)	(0.332)	(520.0)
I.2012*Log(Scope 1) 1	0.0179	-0.000438	-0.00638	0.308	1298.2	-0.944	224.3*	0.160	-1076.3	1.333***	1315.5**
	(0.0347)	(0.0159)	(0.0106)	(1.483)	(891.2)	(2.852)	(119.2)	(0.137)	(1314.3)	(0.403)	(627.8)
I.2013*Log(Scope 1)	0.0294	0.00902	-0.000721	0.472	1311.4	0.716	285.4**	0.239	195.1	1.563***	1729.9**
	(0.0377)	(0.0174)	(0.0117)	(1.740)	(937.9)	(2.287)	(143.2)	(0.150)	(1793.2)	(0.452)	(742.8)
I.2014*Log(Scope 1)	0.0169	0.00764	0.000843	-1.026	1677.6*	1.071	291.1	0.269	-416.3	1.503***	1505.0*
	(0.0386)	(0.0185)	(0.0128)	(1.773)	(918.6)	(3.012)	(191.3)	(0.165)	(1642.0)	(0.477)	(769.3)
I.2015*Log(Scope 1)	0.0561	0.0394*	0.0260*	-0.963	186.5	1.859	58.16	0.454**	-1829.0	1.581***	1772.1**
	(0.0398)	(0.0203)	(0.0142)	(1.914)	(1106.7)	(3.708)	(222.1)	(0.181)	(1747.7)	(0.547)	(877.9)
I.2016*Log(Scope 1)	0.0912**	0.0612***	0.0419***	-2.267	-854.4	-0.956	2.570	0.538***	-2163.0	1.554***	1933.2*
	(0.0411)	(0.0209)	(0.0143)	(1.638)	(1674.5)	(3.931)	(231.2)	(0.197)	(1935.8)	(0.526)	(1051.3)
I.2017*Log(Scope 1)	0.0761*	0.0677***	0.0500***	-1.574	3266.3**	-1.229	262.8	0.480**	-1594.2	1.320**	2307.4**
	(0.0408)	(0.0213)	(0.0149)	(1.465)	(1580.0)	(3.688)	(228.2)	(0.195)	(2201.1)	(0.529)	(1161.3)
I.2018*Log(Scope 1)	0.0528	0.0524**	0.0403***	-1.359	4523.6**	-2.672	431.2**	0.433**	-1401.2	0.896*	1910.0*
	(0.0406)	(0.0209)	(0.0148)	(1.442)	(2083.9)	(3.822)	(215.8)	(0.181)	(2339.1)	(0.541)	(1030.4)
I.2019*Log(Scope 1)	0.0621	0.0464**	0.0341**	-0.940	3956.9*	0.279	652.4**	0.242	-663.8	0.530	2286.9*
	(0.0433)	(0.0226)	(0.0157)	(1.577)	(2034.2)	(3.802)	(273.6)	(0.167)	(3055.8)	(0.572)	(1353.6)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	89999	89999	89999	4276	4276	4276	4276	33877	33877	33877	33877
R^2	0.539	0.751	0.832	0.875	0.939	0.865	0.935	0.907	0.932	0.842	0.933

Note: The dependent variables for columns 1 to 7 are respectively 1-Year EDF,5-Year EDF, 10-Year EDF, Asset Volatility, Market Value of Assets, Market leverage and Default point. We report in the table the coefficient for Log(Scope 1) and 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 Ratio, and Capital Intensity. The Fixed Effects (FE) included are Year and Firm. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table A6. Robustness FE - Before and After the Paris Agreement

PANEL A	**Before Paris Agreement**			**After Paris Agreement**		
	(1)	(2)	(3)	(4)	(5)	(6)
Var. Dep.	1-Year EDF	5-Year EDF	10-Year EDF	1-Year EDF	5-Year EDF	10-Year EDF
log(Scope 1)	-0.0104	-0.0308**	-0.0594***	-0.00558	-0.0182	-0.0448***
	(0.0116)	(0.0122)	(0.0113)	(0.0120)	(0.0133)	(0.0116)
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	N
N	80690	80690	80690	84900	84900	84900
R-Squared	0.0953	0.158	0.280	0.100	0.140	0.217
PANEL B	**Before Paris Agreement**			**After Paris Agreement**		
Var. Dep.	1-Year EDF	5-Year EDF	10-Year EDF	1-Year EDF	5-Year EDF	10-Year EDF
log(Scope 1)	-0.0121	-0.0260*	-0.0482***	-0.0108	-0.0169	-0.0357***
	(0.0129)	(0.0136)	(0.0125)	(0.0125)	(0.0139)	(0.0125)
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
N	80690	80690	80690	84900	84900	84900
R-Squared	0.113	0.187	0.316	0.155	0.218	0.296

Note: To check the robustness of the estimated coefficients, table reports the estimated coefficients of the equation augmented with country and year fixed effects (Panel A) and with country, year and industry fixed effects (Panel B). The table shows that the results are robust only for the 5-year EDF, for all specifications. We find no significant effect for the 1-year EDF and a negative and statistically significant effect for the 10-year EDF, in both sub-periods. This suggests that within industries, firms that emit more have a lower probability of default both before and after 2015. However, we argue that the inclusion of firm fixed effect is fundamental for controlling for unobservable firm's fixed characteristics that may conceal the effect of transition risks. The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The Fixed Effects (FE) included are Year, Country and Firm. The dependent and independent variables are winsorized at the bottom and top 1%. The Pre Paris Agreement subsample spans the years 2011-2014, while the Post Paris Agreement spans the years 2016-2019. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A7. Robustness: Interaction Emission and 1(Post 2015)

Sample	All	All	All	All	1st Quintile	5th Quintile	1st Quintile	5th Quintile	1st Quintile	5th Quintile	1st Quintile	5th Quintile
	Asset Volatility	Market Value of Assets	Market Leverage	Default Point	Asset Volatility		Market Value of Assets		Market Leverage		Default Point	
1(Post 2015)	-5.234***	-15201.4***	-4.115***	-4393.7***	-5.690***	-2.617*	-5741.7***	-14109.3	1.075	8.522*	-548.3**	-11915.3*
	(0.387)	(3040.2)	(0.806)	(593.8)	(1.977)	(1.507)	(1912.5)	(18024.0)	(2.325)	(5.032)	(235.6)	(6937.7)
log(Scope 1)	-0.414***	-475.5	-0.409**	-259.4***	-0.483	-0.328	-349.2	4495.1	0.225	-1.118	-56.68*	-673.2
	(0.104)	(399.3)	(0.198)	(72.08)	(0.316)	(0.256)	(246.8)	(6284.0)	(0.500)	(0.819)	(33.78)	(633.3)
1(Post 2015)*Log(Scope 1)	0.369***	1727.7***	0.157**	448.5***	0.453	0.186*	1042.4***	1340.9	-0.427	-0.764**	111.6***	824.2**
	(0.0331)	(282.0)	(0.0715)	(67.45)	(0.307)	(0.101)	(319.6)	(1158.6)	(0.364)	(0.329)	(38.59)	(410.4)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	165590	165590	165590	165590	32961	33366	32961	33366	32961	33366	32961	33366
R-Squared	0.920	0.888	0.841	0.936	0.920	0.895	0.816	0.923	0.875	0.833	0.900	0.945

Note: The table report the estimated coefficient of the following regression: $\text{EDF Component}_{it} = \alpha + \beta_1 1(\text{Post 2015})_t + \beta_2 \text{Log}(\text{Scope 1})_{it} + \beta_3 1(\text{Post 2015})_t \text{Log}(\text{Scope 1})_{it} + \beta_4 X_{it} + \gamma_i + \epsilon_{it}$ Where $1(Post2015)$ takes value 1 in 2016-2019 and 0 in 2011-2014. The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. We include Firm FE. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A8. Robustness: Interaction Emission and 1(Post 2015) for all quintiles of emissions

Dep. Var.	Asset Volatility					Market Value of Assets					Market Leverage				
Emissions' Quintile	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1(Post 2015)	-5.690***	-1.749	-10.61*	3.602	-2.617*	-5741.7***	-9181.3	-31800.5	-46342.1**	-14109.3	1.075	-3.231	-12.75	-21.73**	8.522*
	(1.977)	(4.133)	(5.457)	(3.580)	(1.507)	(1912.5)	(6600.0)	(47463.7)	(19620.7)	(18024.0)	(2.325)	(8.761)	(13.23)	(10.90)	(5.032)
log(Scope 1)	-0.483	-0.848*	-1.398***	0.0541	-0.328	-349.2	-2006.0**	2802.4	-3189.2*	4495.1	0.225	-1.270	-1.978*	-1.430	-1.118
	(0.316)	(0.459)	(0.460)	(0.428)	(0.256)	(246.8)	(967.3)	(2663.5)	(1687.1)	(6284.0)	(0.500)	(0.988)	(1.119)	(1.228)	(0.819)
1(Post 2015)*log(Scope 1)	0.453	-0.00444	0.926*	-0.339	0.186*	1042.4***	1180.5	3199.4	4256.1**	1340.9	-0.427	0.0798	1.136	1.652*	-0.764**
	(0.307)	(0.472)	(0.530)	(0.303)	(0.101)	(319.6)	(767.7)	(4618.8)	(1665.1)	(1158.6)	(0.364)	(1.004)	(1.304)	(0.921)	(0.329)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Window Event	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]	[-4,+4]
N	32961	32786	33081	33396	33366	32961	32786	33081	33396	33366	32961	32786	33081	33396	33366
R-Squared	0.920	0.889	0.895	0.913	0.895	0.816	0.858	0.888	0.924	0.923	0.875	0.838	0.866	0.832	0.833

Note: The table report the estimated coefficient of the following regression: $\text{EDF Component}_{it} = \alpha + \beta_1 1(\text{Post 2015})_t + \beta_2 \text{Log}(\text{Scope 1})_{it} + \beta_3 1(\text{Post 2015})_t \text{Log}(\text{Scope 1})_{it} + \beta_4 X_{it} + \gamma_i + \epsilon_{it}$. Where $1(Post2015)$ takes value 1 in 2016-2019 and 0 in 2011-2014. The specification is run separately of each quintile of emissions. The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. We include Firm FE. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level. * for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A9. Baseline for quintiles of firm'size

Dep. Var.	1-Year EDF					5-Year EDF					10-Year EDF				
Size's Quintile	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Log(Scope 1)	-0.0977*	-0.133***	-0.0830	-0.0566	-0.183**	-0.0823**	-0.0970***	-0.0362	-0.0403	-0.0771*	-0.114***	-0.0827***	-0.0363	-0.0331	-0.0584**
	(0.0586)	(0.0435)	(0.0569)	(0.0727)	(0.0850)	(0.0408)	(0.0293)	(0.0335)	(0.0478)	(0.0407)	(0.0337)	(0.0243)	(0.0252)	(0.0351)	(0.0286)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46878	47281	46906	46964	45537	46878	47281	46906	46964	45537	46878	47281	46906	46964	45537
r2	0.450	0.470	0.513	0.451	0.387	0.677	0.711	0.735	0.659	0.608	0.761	0.790	0.805	0.750	0.713

Note: The baseline regression is run separately for each quintile of firm's size (defined as log(total assets)). The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample spans the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and *** for $p < 0.01$.

Table A10. Forward Looking Transition Risk with Firm FE

	(1) 10-Year EDF	(2) 10-Year EDF	(3) 10-Year EDF	(4) 10-Year EDF	(5) 10-Year EDF	(6) 10-Year EDF	(7) 10-Year EDF	(8) 10-Year EDF	(9) 10-Year EDF
log(Scope 1)	-0.00391	-0.00428	-0.00435	-0.0264	-0.0272	-0.0268	-0.148*	-0.154*	-0.153*
	(0.0382)	(0.0382)	(0.0382)	(0.0434)	(0.0437)	(0.0436)	(0.0871)	(0.0899)	(0.0911)
FLR Low	0.00378			0.0340			0.00162		
	(0.00234)			(0.0401)			(0.00226)		
FLR Medium		0.00207*			0.0133			0.00114	
		(0.00111)			(0.0240)			(0.00116)	
FLR High			0.00122*			0.00818			0.000588
			(0.000678)			(0.0120)			(0.000711)
Emission Quintiles	All	All	All	1st	1st	1st	5th	5th	5th
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.906	0.906	0.906	0.917	0.917	0.917	0.939	0.939	0.939
N	51849	51849	51849	8473	8473	8473	11291	11291	11291

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2017 to 2019. FRL stands from Forward Looking Risk calculated as the additional financial cost that a company could face due to possible future carbon pricing. This is calculated for each firms based on its sector, operations, and a given price policy scenario (low, medium and high). For the analysis we use firm's carbon earnings at risks as percentage of EBITDA for both Low, Medium and High policy scenarios in 2030. The log(Scope 1) and 10-Year EDF variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

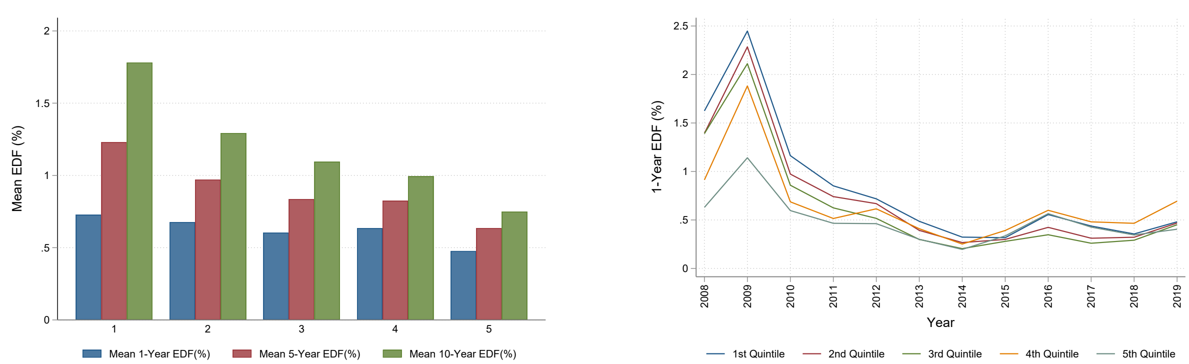
Table A11. Rate of Change of Scope 1 Emission

	(1) 1-Year EDF	(2) 5-Year EDF	(3) 10-Year EDF	(4) 1-Year EDF	(5) 5-Year EDF	(6) 10-Year EDF
$\Delta log(Scope1)$	-0.00281	0.00161	0.00585***	-0.00421*	-0.00172	0.000539
	(0.00246)	(0.00177)	(0.00170)	(0.00216)	(0.00120)	(0.00107)
Firm-level controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	N	N	N
Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
N	217903	217903	217903	217903	217903	217903
R-Squared	0.143	0.190	0.288	0.400	0.668	0.780

Note: The dependent variable is $\Delta log(Scope1)$ constructed as $(log(Scope1)_t - log(Scope1)_{t-1}/log(Scope1)_{t-1}) * 100$. The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The Fixed Effects (FE) included are Year, Country, Industry and Firm FE. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Figure A2. Mean EDF by first year quintile of Log(Scope 1)



(a) Entire Sample

(b) Over Time for 1-Year EDF

Table A12. Baseline Result using Relative Emission

Panel A:	**1Y-EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Intensity	-0.0000419	0.0000217	-0.000123*	-0.0000469	0.0000165	-0.000165**
	(0.0000317)	(0.0000368)	(0.0000717)	(0.0000353)	(0.0000384)	(0.0000703)
R-Squared	0.0703	0.0803	0.358	0.126	0.141	0.386
Panel B:	**5Y-EDF**					
Carbon Intensity	-0.0000886***	-0.00000334	-0.0000113	-0.0000307	0.0000356	-0.0000410
	(0.0000281)	(0.0000332)	(0.0000655)	(0.0000314)	(0.0000348)	(0.0000625)
R-Squared	0.0306	0.0593	0.614	0.149	0.189	0.645
Panel C:	**10Y-EDF**					
Carbon Intensity	-0.000170***	-0.0000625**	0.00000627	-0.0000399	0.0000220	-0.0000151
	(0.0000234)	(0.0000286)	(0.0000508)	(0.0000261)	(0.0000298)	(0.0000471)
R-Squared	0.0327	0.0732	0.737	0.237	0.288	0.764
Firm-level controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	N	Y	Y	N
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	243718	243718	243718	233566	233566	233566

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorized at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A13. Result - Lagged Variables

	(1) 1-Year EDF	(2) 5-Year EDF	(3) 10-Year EDF	(4) 1-Year EDF	(5) 5-Year EDF	(6) 10-Year EDF
$log(Scope1)_{t-1}$	-0.0107	-0.0206*	-0.0435***			
	(0.0123)	(0.0120)	(0.0110)			
$log(Scope1)_{t-2}$				-0.00216	-0.0129	-0.0370***
				(0.0103)	(0.0117)	(0.0109)
Year, Country & Industry FE	Y	Y	Y	Y	Y	Y
Firm-Level Controls	Y	Y	Y	Y	Y	Y
N	217903	217903	217903	196515	196515	196515
R-Squared	0.143	0.190	0.291	0.134	0.192	0.291

	(1) 1-Year EDF	(2) 5-Year EDF	(3) 10-Year EDF	(4) 1-Year EDF	(5) 5-Year EDF	(6) 10-Year EDF
$log(Scope1)_{t-1}$	-0.0688**	-0.0532***	-0.0712***			
	(0.0296)	(0.0194)	(0.0160)			
$log(Scope1)_{t-2}$				-0.00427	-0.000512	-0.0252*
				(0.0201)	(0.0174)	(0.0143)
Year & Firm FE	Y	Y	Y	Y	Y	Y
Firm-Level Controls	Y	Y	Y	Y	Y	Y
N	217903	217903	217903	196515	196515	196515
R-Squared	0.400	0.669	0.781	0.538	0.720	0.808

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The dependent and independent variables are winsorized at the bottom and top 1%. The sample spans the years from 2008 to 2019. Standard errors in parentheses are are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A14. Ratings, Sector and Public Ownership

	Ratings		Green Sector		Ownership		Ratings		Green Sector		Ownership	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Panel A: 1-Year EDF												
Log(Scope 1)	-0.00629	-0.117**	-0.0647	0.0800**	0.0439	-0.0341**	-0.0304**	-0.334***	-0.0851	-0.121	-0.0377	-0.155***
	(0.00611)	(0.0476)	(0.0593)	(0.0321)	(0.0299)	(0.0149)	(0.0134)	(0.112)	(0.0771)	(0.0973)	(0.0569)	(0.0293)
R-Squared	0.135	0.207	0.182	0.226	0.339	0.141	0.484	0.475	0.393	0.477	0.487	0.386
Panel B: 5-Year EDF												
Log(Scope 1)	-0.0138**	-0.0835**	-0.0537	0.0776***	0.0632	-0.0367***	-0.0280**	-0.198**	-0.072	-0.0502	-0.0392	-0.0961***
	(0.00642)	(0.0397)	(0.0465)	(0.0268)	(0.042)	(0.0134)	(0.012	(0.0803)	(0.0441)	(0.0591)	(0.0506)	(0.0189)
R-Squared	0.173	0.208	0.246	0.35	0.507	0.192	0.702	0.679	0.649	0.692	0.715	0.648
Panel C: 10-Year EDF												
Log(Scope 1)	-0.0245***	-0.0762**	-0.0759*	0.0440*	0.0564	-0.0543***	-0.0304**	-0.141**	-0.0877**	-0.0495	-0.0332	-0.0917***
	(0.0075)	(0.032)	(0.0396)	(0.0226)	(0.0413)	(0.0121)	(0.0119)	(0.0579)	(0.0365)	(0.0455)	(0.0387)	(0.0153)
N	50854	38586	39758	31653	5821	217413	50853	38584	39758	31653	5821	217413
R-Squared	0.277	0.253	0.383	0.42	0.64	0.297	0.827	0.761	0.765	0.778	0.841	0.766
Year, Country and Industry	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N
Year and Firm	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y

Note: The table reports the estimated coefficients of the baseline regression divide by ratings, sector and public ownership with Year, Industry, Country and Firm FE. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.05$, ** for $p < 0.01$ and for *** $p < 0.001$.

Table A15. Baseline Result with Month-Year Fixed Effects

Panel A:	**1Y-EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-0.0355***	-0.0452***	-0.116***	-0.0262**	-0.0236*	-0.148***
	(0.00716)	(0.00835)	(0.0287)	(0.0130)	(0.0136)	(0.0294)
R-Squared	0.0992	0.110	0.385	0.150	0.164	0.410
Panel B:	**5Y-EDF**					
log(Scope 1)	-0.0751***	-0.0907***	-0.116***	-0.0339***	-0.0271**	-0.0919***
	(0.00702)	(0.00844)	(0.0199)	(0.0116)	(0.0123)	(0.0184)
R-Squared	0.0637	0.0953	0.621	0.154	0.193	0.650
Panel C:	**10Y-EDF**					
log(Scope 1)	-0.127***	-0.146***	-0.134***	-0.0586***	-0.0462***	-0.0874***
	(0.00672)	(0.00815)	(0.0170)	(0.0104)	(0.0111)	(0.0149)
R-Squared	0.135	0.176	0.742	0.247	0.293	0.766
Firm-level controls	N	N	N	Y	Y	Y
Month-Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	243718	243718	243718	233566	233566	233566

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorize at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A16. Baseline Result without Utilities Sectors

Panel A:	**1Y-EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-0.0272***	-0.0455***	-0.0967***	-0.0244*	-0.0287*	-0.134***
	(0.00805)	(0.00883)	(0.0271)	(0.0139)	(0.0150)	(0.0281)
R-Squared	0.0741	0.0838	0.358	0.130	0.141	0.387
Panel B:	**5Y-EDF**					
log(Scope 1)	-0.0689***	-0.0936***	-0.108***	-0.0338***	-0.0334**	-0.0864***
	(0.00801)	(0.00908)	(0.0196)	(0.0124)	(0.0137)	(0.0185)
R-Squared	0.0489	0.0803	0.613	0.148	0.182	0.643
Panel C:	**10Y-EDF**					
log(Scope 1)	-0.124***	-0.151***	-0.131***	-0.0602***	-0.0525***	-0.0855***
	(0.00773)	(0.00880)	(0.0168)	(0.0111)	(0.0124)	(0.0151)
R-Squared	0.114	0.157	0.736	0.236	0.280	0.761
Firm-level controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	230487	230487	230487	220635	220635	220635

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorize at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A17. Baseline Result without Manufacturing Sectors

Panel A:	**1Y-EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-0.0294***	-0.0436***	-0.116***	-0.0191	-0.00901	-0.127***
	(0.00935)	(0.0126)	(0.0405)	(0.0179)	(0.0188)	(0.0400)
R-Squared	0.0690	0.0868	0.374	0.121	0.145	0.395
Panel B:	**5Y-EDF**					
log(Scope 1)	-0.0653***	-0.0881***	-0.116***	-0.0188	-0.00622	-0.0739***
	(0.00860)	(0.0116)	(0.0272)	(0.0158)	(0.0163)	(0.0242)
R-Squared	0.0586	0.110	0.623	0.143	0.208	0.647
Panel C:	**10Y-EDF**					
log(Scope 1)	-0.116***	-0.146***	-0.131***	-0.0391***	-0.0238*	-0.0722***
	(0.00805)	(0.0109)	(0.0235)	(0.0141)	(0.0144)	(0.0201)
R-Squared	0.133	0.198	0.737	0.248	0.324	0.760
Firm-level controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	129008	129008	129008	123372	123372	123372

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorize at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.

Table A18. Baseline Result at the Yearly level

Panel A:	**1Y-EDF**					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Scope 1)	-0.0362***	-0.0461***	-0.115***	-0.0264**	-0.0243*	-0.152***
	(0.00709)	(0.00829)	(0.0286)	(0.0128)	(0.0135)	(0.0291)
R-Squared	0.0930	0.106	0.452	0.152	0.171	0.482
Panel B:	**5Y-EDF**					
log(Scope 1)	-0.0764***	-0.0922***	-0.116***	-0.0349***	-0.0283**	-0.0957***
	(0.00697)	(0.00840)	(0.0199)	(0.0115)	(0.0123)	(0.0187)
R-Squared	0.0681	0.101	0.665	0.161	0.202	0.693
Panel C:	**10Y-EDF**					
log(Scope 1)	-0.128***	-0.147***	-0.134***	-0.0596***	-0.0472***	-0.0907***
	(0.00669)	(0.00813)	(0.0171)	(0.0103)	(0.0111)	(0.0152)
R-Squared	0.145	0.187	0.772	0.257	0.305	0.793
Firm-level controls	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	N	Y	N
Firm FE	N	N	Y	N	N	Y
N	20659	20659	20659	20096	20096	20095

Note: The controls included are Size, Debt Ratio, Operating Margin Ratio and Capital Intensity. The sample span the years from 2008 to 2019. The dependent and independent variables are winsorize at the bottom and top 1%. Standard errors in parentheses are clustered at the firm level.

* for $p < 0.10$, ** for $p < 0.05$ and for *** $p < 0.01$.