Greening the Red: Climate Transition Risk and Corporate Bankruptcy *

Matilde Faralli and Costanza Tomaselli †

January 8, 2025

Abstract

We examine the relationship between bankruptcy and climate risk. Using a novel dataset of business bankruptcies from 2000 to 2023, linked with environmental indicators, we find that firms exposed to higher climate risks, particularly brown companies, are more prone to financial distress and bankruptcy filings. We also document that brown firms frequently opt for reorganization over liquidation, reflecting both financial and strategic considerations. To address potential endogeneity in bankruptcy choices, we exploit the random assignment of bankruptcy judges to evaluate the differential impact of bankruptcy decisions on post-bankruptcy environmental performance. Leveraging facility-level emissions data, we show that facilities assigned to a more lenient bankruptcy judge exhibit lower emissions post-bankruptcy compared to those assigned to a stricter judge. Our results suggest that reorganization enables firms to reduce emissions through debt relief, which improves financial flexibility and facilitates green investments.

Keywords: Financial Distress, Corporate Bankruptcies, Climate Risks, Post-bankruptcy Asset Utilization.

JEL Codes: G33, Q56, K41

*We thank Claudia Custodio, Marcin Kacperczyk, Mirabelle Muûls, Simon Quinn, John Finlay, Karmini Sharma, Andre Veiga, Alex Michaelides, Ivo Welch, the discussant Richard Sweeney and Alvin Lumbanraja, seminar participants at the Harvard Climate Economics Pipeline Workshop, Interdisciplinary PhD Workshop in Sustainable Development (IPWSD) at Columbia University, POID LSE Seminar, Climate Workshop at Bank of Italy, 7^{th} Dauphine Finance PhD Workshop, Comparative Analysis of Enterprise Data (CAED) at Penn State University, 6^{th} JRC Summer School on Sustainable Finance, QMUL 6^{th} PhD Conference, 4^{th} WE ARE IN Macroeconomics and Finance Conference, and Imperial Student Seminar for their comments. We thank the Essex Finance Centre Banking and Finance and the IFABS 2024 Conferences for the Best PhD Paper Award. We gratefully acknowledge the financial support provided by Franklin Allen and the Imperial College Business School for this project. We also like to thank Ben Schlafman from BankruptcyData for his help and patience with our questions on data collection.

†Imperial College Business School

1 Introduction

Climate change imposes significant economic risks, disrupting infrastructure, straining supply chains, and increasing operational costs. Beyond these direct impacts, climate transition risks, such as the potential introduction of carbon pricing and stricter emissions regulations, create challenges that are particularly acute for high-emission industries (TCFD, 2017). While prior research has explored climate transition risks' impact on production (Colmer et al., 2024), financing (Kacperczyk and Peydro, 2024), and management (TCFD, 2017), relatively little is known about the intersection of climate risks and corporate bankruptcies, despite bankruptcies plays a pivotal role in reallocating economic resources, restructuring firms, and addressing financial instability.

This question is particularly relevant given recent trends. Corporate bankruptcies in the U.S. surged to their highest level since 2010 by December 2023.[1] Bankruptcy serves as a mechanism to address insolvency, ideally reorganizing viable firms and liquidating unproductive ones to optimize resource allocation. However, while bankruptcy outcomes are typically evaluated using financial metrics such as creditor repayment, less attention has been given to whether the process also advances environmental objectives. As climate risks increasingly shape firm behavior, their influence on bankruptcy outcomes merits closer scrutiny.

We make three primary contributions. First, we provide evidence that firms exposed to greater climate risks, particularly high-emission or *brown* firms, are more likely to experience financial distress and to file for bankruptcy. Second, we show that *brown* firms are more likely to reorganize under Chapter 11 and tend to experience shorter bankruptcy processes. While these initial analyses are correlational, our third contribution, by leveraging exogenous variation from the random assignment of bankruptcy judges, discovers that facilities of firms assigned to more lenient judges exhibit lower emissions in the post-bankruptcy period compared to those of firms assigned to stricter judges, suggesting that reorganization may better support environmental objectives.

To begin, we analyze whether firms exposed to varying levels of climate risk are more likely to experience financial distress and file for bankruptcy. We construct a comprehensive dataset of active and inactive U.S. firms from Orbis, matched with *BankruptcyData*, covering corporate bankruptcies from 2000 to 2023. Firms are classified as

[1] Source: https://www.spglobal.com/article

brown or *green* based on business descriptions, following the methodology of Giannetti et al. (2023). Financial distress is measured using the Altman Z-score, and bankruptcy likelihood is estimated with a probit model incorporating firm-level characteristics.

By examining differences in financial distress and estimated bankruptcy probabilities between *brown* and *green* companies, our findings indicate that higher climate risks are associated with greater financial distress and an increased likelihood of bankruptcy, consistent with prior studies (Seltzer et al., 2022; Ilhan et al., 2021; Blasberg et al., 2021; Carbone et al., 2021).

Next, we investigate the bankruptcy paths taken by firms with varying environmental indicators—Chapter 11 reorganization versus Chapter 7 liquidation—and analyze the associated costs. For this analysis, we supplement *BankruptcyData* with the Federal Judicial Center database, which provides comprehensive information on federal cases, including bankruptcies. Using a probit model, we regress a binary indicator for reorganization versus liquidation choices on climate risk exposure, controlling for firm characteristics. Our results indicate that brown firms, facing higher environmental risks, are more likely to choose reorganization and tend to undergo shorter bankruptcy processes.

Lastly, we employ the exogenous allocation of judges to evaluate whether firms assigned to a stricter judge demonstrate greater efficiency in asset utilization with respect to post-bankruptcy emissions. Using facility-level emissions data from the EPA, which mandates annual reporting of greenhouse gases by large emitters, we examine emissions dynamics before and after bankruptcy. This sample focuses on large, high-emission firms, setting an upper bound for the observed effects.

Analyzing changes in facility total emissions over three years before and after bankruptcy, we observe a general decline in emissions post-bankruptcy filings. To address the endogeneity of bankruptcy decisions, we follow the bankruptcy literature (Aloisio et al., 2023), by constructing an exogenous measure of the likelihood of reorganization based on judge assignment.

For each judge, we develop a *continuation bias* score reflecting the probability of a firm remaining operational five years post-bankruptcy. This judge bias positively correlates with firms' reorganization likelihood and lower emissions post-bankruptcy. Consistent with our earlier results, facility emissions decrease post-bankruptcy more significantly for firms assigned to more lenient judges than for firms assigned to stricter ones.

We propose three mechanisms to explain the observed emission reductions: *debt relief, asset specificity, and facility under-utilization*. First, reduced debt enables brown firms to allocate resources toward sustainable practices (Hartzmark and Shue, 2023). Second, facilities with specific assets perform better under continued ownership (Bernstein et al., 2019), while ownership changes can lead to inefficiencies and poorer environmental outcomes (Williamson, 1988; Kermani and Ma, 2022). Lastly, under-utilized facilities post-bankruptcy present opportunities for greener technology adoption, improving environmental performance (Bernstein et al., 2019).

We rule out the *under-utilization* mechanism, as bankrupted facilities show no significant differences in sales and employment. Notably, when emissions are scaled by assets, the results are very similar to those based on total emissions. However, our findings support the *debt relief* mechanism, with reorganized firms experiencing substantial debt reduction, especially for brown companies. While data constraints limit our ability to fully assess *ownership changes*, these findings underscore the significant impact of bankruptcy proceedings on a firm's environmental footprint.

In summary, our findings suggest that bankruptcy could enhance environmental performance, with debt reduction playing a pivotal role. Given that brown firms face greater financial distress and are more likely to reorganize, our findings imply that the bankruptcy process could contribute positively to climate change mitigation efforts.

We contribute to three key areas within the existing literature. First,we extend the growing body of literature on the financial implications of climate risks by being the first, to our knowledge, to document their impact on the probability of bankruptcy. Prior studies have shown that climate transition risks influence financial metrics on various financial metrics such as yield spreads (Seltzer et al., 2022), option-implied volatility slope (Ilhan et al., 2021), CDS spreads (Blasberg et al., 2021), market implied distance to default (Capasso et al., 2020; Carbone et al., 2021; Kabir et al., 2021), and Moody's EDF (Faralli and Ruggiero, 2022). Consistent with these findings, we demonstrate that climate risks are reflected in heightened probabilities of financial distress and default. By linking climate risks to the likelihood of bankruptcy, we contribute to the broader understanding of how environmental factors shape corporate solvency and economic resilience.

Second, to the best of our knowledge, this study is the first to examine how climate risks influence the bankruptcy process itself. We illustrate how climate factors can play a

role in both reorganization procedures like Chapter 11 (e.g., Baird, 1986; Aghion et al., 1992; Hotchkiss, 1995) and liquidations like Chapter 7 (e.g., Shleifer and Vishny, 1992; Pulvino, 2002; Strömberg, 2000; Thorburn, 2000). Our results suggest that brown firms are more likely to file for Chapter 11 and to face lower bankruptcy costs (i.e., shorter proceedings).

Third, we investigate how judicial bias in the application of bankruptcy law influences environmental outcomes. Previous research has emphasized the role of market conditions (Bernstein et al., 2019), conflicts of interest among claim holders (Baird, 1986), and coordination costs (Ivashina et al., 2016) in determining efficient post-bankruptcy asset allocation. Building on the concept of pro-continuation judicial bias as discussed in Aloisio et al. (2023), we provide novel evidence that judicial bias favoring reorganization can yield positive environmental outcomes. Specifically, we show that firms assigned to more lenient judges are more likely to exhibit lower emissions post-bankruptcy. This reduction is not attributable to a decline in sales or workforce but rather to debt relief, which enables firms to invest in environmentally sustainable practices.

The paper is structured as follows. Section 2 discusses the US bankruptcy procedure. Section 3 covers the data and descriptive statistics. Section 4 explores correlations, examining if brown firms are more prone to distress, their bankruptcy filing choices, and related costs. Section 5 analyzes facility emissions post-bankruptcy, employing a quasi-experiment using random judge assignments to address endogeneity. Section 6 concludes.

2 Institutional Setting

In the United States, the bankruptcy process is governed by federal law under the U.S. Bankruptcy Code. The primary objective of bankruptcy is to offer a fresh start to distressed entities while ensuring equitable treatment for creditors. The following section provides an overview of how bankruptcy works for firms in the U.S., with a particular focus on Chapter 7 and Chapter 11 bankruptcies.

Chapter 7 Bankruptcy. Also known as liquidation, Chapter 7 is primarily intended for businesses that are unable to continue their operations and need to liquidate their assets to pay off creditors. The firm files a voluntary petition for bankruptcy in a federal bankruptcy court. Creditors can also initiate an involuntary petition to force a

company into Chapter 7 if they believe it is necessary.

Once the petition is filed, an automatic stay is immediately enacted. This stay halts all collection activities by creditors, providing temporary relief to the debtor. The court then appoints a bankruptcy trustee whose role is to oversee the liquidation of the company's assets.

Chapter 7 is generally viewed as a last resort for firms that are deemed non-viable, particularly when no feasible reorganization plan can be achieved. The process is relatively quick and straightforward, providing a resolution that allows for the redistribution of assets to more productive uses in the economy (Baird, 2020).

Chapter 11 Bankruptcy. Often referred to as reorganization, Chapter 11 is designed for businesses that have the potential to remain viable by restructuring their debts and operations. Similarly to Chapter 7, it starts with the filing of a voluntary or involuntary petition and the enactment of an automatic stay to prevent creditor actions.

One of the key features of Chapter 11 is that the debtor typically remains in control of the business as a "debtor in possession" (DIP). The DIP continues to operate the business and is responsible for developing a reorganization plan, which involves negotiating with creditors. Unlike Chapter 7, the focus is on preserving the value of the firm as a going concern rather than liquidating its assets. For the plan to be confirmed, it must meet several criteria, including feasibility, good faith, and the best interest of creditors.

Once the reorganization plan is confirmed, the debtor begins implementation, often by streamlining operations, selling non-core assets, or renegotiating debts. Importantly, Chapter 11 provides firms with the opportunity to address long-term strategic challenges, including environmental and operational inefficiencies, which could enhance both financial and non-financial performance post-bankruptcy. The goal is to allow the company to emerge from bankruptcy as a healthier and more viable business. If successful, the remaining debts may be discharged at the end of the process, allowing the firm to continue operations with a more sustainable financial structure (LoPucki, 2008).

3 Data and Descriptive Statistics

Firms' information. We start our research by gathering data on the entire universe of private and public companies in Orbis, covering both active and inactive firms. We discard non-US firms and those in financial sectors. We complement this data with various financial metrics for these companies, such as total assets, cash reserves, total debt, total liabilities, total revenue, retained earnings, EBIT, EBITDA, and total equity. We also obtain the firm's establishment date, when missing, we estimate it based on the earliest year with available data from Orbis. The final sample comprises 11,641 firms.[2]

Corporate Bankruptcies. We construct a comprehensive dataset of US corporate bankruptcies spanning 2000 to 2023 using the "Bankruptcydata.com" (BD) database from New Generation Research. Focusing solely on Chapters 7 and 11, the BD contains approximately 570,000 bankruptcy cases. In particular, it includes the following information: (i) the docket number; (ii) the bankruptcy judge; (iii) the filing district; (iv) the filing date; (v) the termination date; (vi) information about the company at the time of filing. We also collect further bankruptcy information using the Federal Judicial Center Integrated Database from WRDS, which complements data when necessary and provides details on creditors.[3]

We proceed by matching the BD with the Orbis dataset.[4] Since Orbis identifiers are the Employer Identification Numbers (EIN), we start by matching BD and Orbis by EIN. However, as almost half of the BD records lack an EIN, we implement a multi-stage name-matching approach. We cleanse the company names by removing punctuation and common business terms before conducting another matching round. To ensure accuracy, we retain only matched firms that are located in the same state.

The final Orbis-BD merged dataset consists of 11,189 firms, with 1,252 having declared bankruptcy. For a smaller number of bankruptcies in the BD dataset, we also have the precise closing date of the bankruptcy case, which includes 1076 firms.

[2]Section D of the Appendix, we replicate our results using S&P Capital IQ. Although S&P Capital IQ offers broader coverage, there are numerous firms with missing fundamental data. Nevertheless, our results remain robust.

[3]FCJ does not provide any company identifiers; thus, the two datasets are merged by the docket ID, filing date, and court state.

[4]See section C.1 in the Appendix for a detailed explanation of this matching process.

Firms' Climate Risks. To assess firms' climate risks, we categorize firms into distinct groups—green, brown, or grey—based on their corporate descriptions from S&P Capital IQ. We use the dictionary provided by Giannetti et al. (2023), as reported in Appendix F, to define firms' climate risks. A firm is defined as brown (green) if its business description contains any brown (green) terminology. Firms identified as grey do not include any of the pre-established dictionary words within their descriptions.

Since we want to track asset emission post-bankruptcy, we gather facility-level data from the Environmental Protection Agency's Greenhouse Gas Reporting Program (GHGRP).[5] A facility is mandated to report its annual emissions if it emits 25,000 metric tons or more of greenhouse gases (GHGs) per year; if it is a certain supplier of fossil fuels, industrial GHGs, and products containing GHGs; or if it injects CO2 underground. For our analysis, we will utilize both Total GHG Emissions and CO2 Emissions.

The data allows us to track facilities over time; even if the company that owns a facility goes bankrupt, we can continue tracking it as long as it remains operational and continues to emit. Using the matching procedure described earlier, we link our dataset by facility or parent company name to the bankruptcy firm. Our facility-level sample comprises 87 bankrupted firms with 434 facility data points. Of these, 70 are reorganized companies (with 358 facilities) and 17 are liquidated (with 76 facilities).[6]

While a company's business description is our preferred variable for the company-level analysis, in the Appendix, we replicate our results by classifying firms into sectors with high and low sensitivity to climate change, based on the carbon emissions associated with each sector as reported by the Intergovernmental Panel on Climate Change (IPCC). This method, while allowing comprehensive coverage across industries, does not provide information on risk heterogeneity within sectors. For this reason, we gather Scope 1 absolute emissions data from Trucost, which are direct greenhouse gas (GHG) emissions that occur from sources controlled or owned by an organization. We then sort firms into high- or low-transition risk categories based on their quintile ranking within each year in our final sample.[7] Importantly, we report our results using different definitions, as the brown sector, large emitters, and brown firms based on business

[5] See https://www.epa.gov/ghgreporting.

[6] Note that these may not necessarily be companies covered in Orbis or the Federal Judicial Center Integrated Database.

[7] If we construct quintiles of emissions in the universe of Trucost emissions, we only merge a small sample of firms as small emitters, thus we decided to re-estimate it within the sample.

descriptions show weak correlations, as shown in Table B2.

3.1 Descriptive Statistics

In our analysis, we primarily use three samples: (i) the Orbis universe combined with *BankruptcyData*, (ii) *BankruptcyData* supplemented with Federal Judicial Center information, and (iii) *BankruptcyData* paired with facility emissions data.

Table 1 presents descriptive statistics for the main variables used in our analysis (Table B1 provides variable descriptions). Panel A shows that, based on fundamentals, bankrupt and non-bankrupt companies in our sample are quite similar, with the exception that bankrupt companies have higher debt, higher liabilities, and lower EBIT. Panel B, which examines bankruptcy cases by process length, confirms that, as expected, Chapter 7 cases tend to be shorter, concluding in about one year, while Chapter 11 cases take approximately two and a half years.

Table 1: Summary statistics

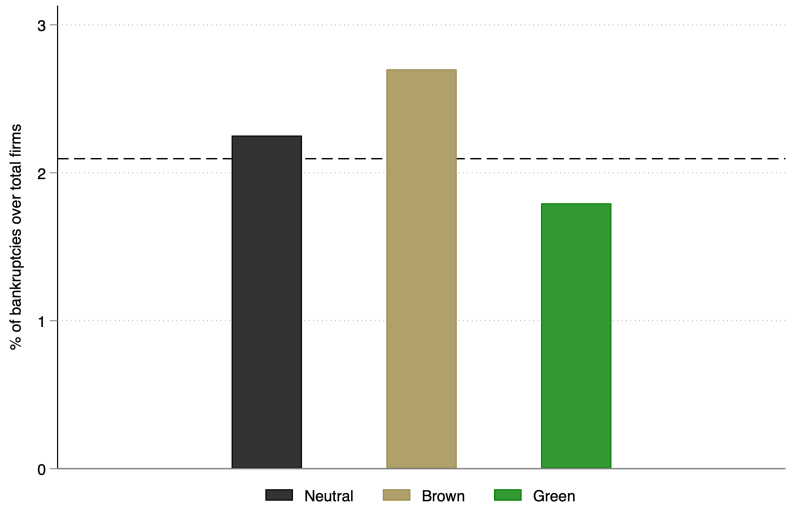
Panel A:	**Probability of Default and Distress**							
Variable	Not Bankrupted (N = 9,937)				Bankrupted (N = 1,252)			
	Median	Std. Dev.	Min	Max	Median	Std. Dev.	Min	Max
Net Income/Assets	-0.01	3854.19	-705297	404034	-0.04	2075.57	-203402	2321
Size	18.55	3.83	0	27.41	19.05	3.13	2	26
Debt ($m)	6.79	2875.57	-74.96	398382	11.569	3420.477	0	208739
Debt/Ebitda	1.28	305.75	-53199	65615	1.84	307.32	-4499	33313
Cash/Asset	0.13	0.29	-1.06	1.28	0.08	0.25	-0.00	1
Age	11	21.58	0	247	12	20.41	0	167
EBIT ($ m)	0.15	1627.33	-56605	119437	-0.07	1018.54	-18583	32936
Total Assets ($ m)	106	16190.27	-0.04	797769	180	12184	0	482347
Sales ($ m)	86	12750.72	-519	611289	157	7431	-0.01	204467
Market Equity ($ m)	44	5708.53	-85560	256144	33	2966	-86154	76804
Total Liabilities ($ m)	37	11725.39	-12	693104	90	10798	-111	459503
Working Capital ($ m)	10.70	2916.28	-89108	270005	12.78	1899.98	-45978	120971
Retained Earnings ($ m)	48.66	5682.28	-190250	251455	47.59	2904.77	-48527	84083

Panel B:	**Length of Bankruptcy**							
Sample	Chapter 11 (N = 506)				Chapter 7 (N = 570)			
	Median	Std. Dev.	Min	Max	Median	Std. Dev.	Min	Max
Log(process length in days)	333	259	6	1,548	162	273	18	1,243

Note: The table reports the summary statistics for the three datasets used in the study: (i) the Orbis universe combined with *BankruptcyData* (Panel A), (ii) *BankruptcyData* supplemented with Federal Judicial Center information (Panel B). *Panel A* consists of the Orbis dataset merged with the bankruptcy data, showing key descriptive statistics for the control variables used in Equations 1 and 2. *Panel B* includes our bankruptcy data merged with climate indicators and reports the length of bankruptcy (in days) by bankruptcy filing type. The closing date was matched with the Federal Judicial Center dataset using the unique case number; observations without a match were excluded from this part of the analysis.

Figure 1 provides a breakdown of firm bankruptcies in Orbis (Panel A) by the share of bankruptcies within each business description category (neutral, green, and brown), with the dotted black line indicating the overall sample average. The figure highlights that brown firms are more likely to file for bankruptcy compared to those in neutral or green firms. In Figure A1, panel (a) shows a breakdown by sector and indicates that green and brown sectors have an equal likelihood of bankruptcy. However, panel (b) shows that the majority of total bankruptcies occur in the manufacturing sector, followed by the information and mining sectors.

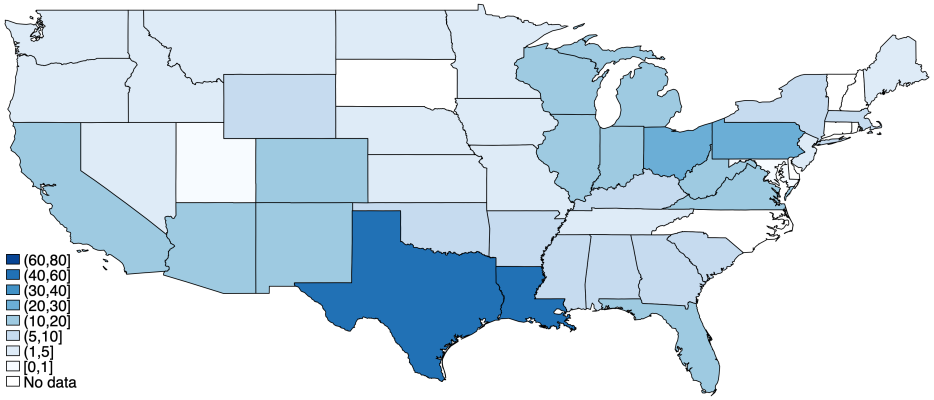
Figure 1: Bankruptcies share by business description



Note: This figure illustrates the share of companies that filed for bankruptcies within a specific business description - neutral, green or brown - over the total sample. This ratio is calculated as the number of firms that declared bankruptcy in the matched samples from Orbis and DB, divided by the total number of firms in the Orbis sample. The dashed line indicates the proportion of bankrupted firms in the overall sample.

When looking at facilities-level data, Figure 2 pinpoints the locations of facilities associated with companies that declared bankruptcy during the period of our analysis. Notably, a significant portion of the facilities are located in Texas and Louisiana, which is consistent with industry trends shown in Figure 1, where a substantial fraction of bankruptcies is observed in brown sectors. This alignment highlights the sector-specific vulnerabilities and geographic heterogeneity in the bankruptcy landscape in our sample period.

Figure 2: Facilities of bankrupted companies mapped by state



Note: This figure shows the unique number of facilities that match our bankruptcy dataset by U.S. state.

4 Facts about Transition risks in Bankruptcy

4.1 Do Climate Risks Affect a Firm's Probability of Bankruptcy?

While several studies have explored the link between climate and credit risks (such as Seltzer et al., 2022; Ilhan et al., 2021; Blasberg et al., 2021; etc.), our research uses our comprehensive dataset of Orbis companies matched to BD bankruptcies to examine the impact of climate risks on a firm's likelihood of financial distress and insolvency. It is important to note that in this section we are showing correlation insights and not causal results; the aim is to primarily represent an exploratory effort to uncover key patterns within our dataset.

Financial Distress. We start by quantifying financial distress by implementing the well-established Altman Z-score method (Altman, 2013). The AZ-score for each firm i in a given year t is computed using the following formula:

$$\begin{aligned} AZ\text{-score}_{i,t} = 1.2 \times \left(\frac{\text{Working Capital}}{\text{Total Assets}}\right)_{i,t} + 1.4 \times \left(\frac{\text{Retained Earnings}}{\text{Total Assets}}\right)_{i,t} \\ + 3.3 \times \left(\frac{\text{EBIT}}{\text{Total Assets}}\right)_{i,t} + 0.6 \times \left(\frac{\text{Market Value of Equity}}{\text{Total Liabilities}}\right)_{i,t} \\ + 0.99 \times \left(\frac{\text{Sales}}{\text{Total Assets}}\right)_{i,t} \end{aligned} \tag{1}$$

While the AZ-Score can range from $-\infty$ to $+\infty$, firms are typically classified as financially distressed at time $t+1$ if their AZ-Score at time t is below 1.8. Firms with scores between 1.8 and 3 are classified as being in a grey zone, and those above 3 are considered safe. For simplicity, we define firms with scores below 1.8 as distressed (value 1) and all others as non-distressed (value 0). To ensure comparable probabilities, we regress this indicator on year and sector fixed effects.[8]

Probability of Default. To assess a firm's likelihood of bankruptcy, we exploit our extensive dataset comprising both active and inactive firms. We use a probit regression to predict the probability of default for firms based on their financial fundamentals as follows:

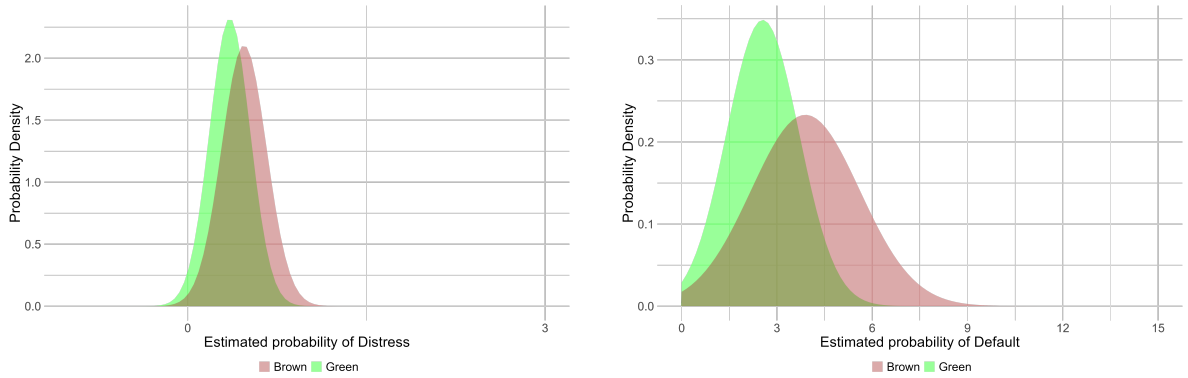
$$\Pr(\text{Bankrupted}_{i,t+1} = 1) = \Phi\Bigg(\alpha + \beta_1 \frac{\text{Net Income}}{\text{Asset}}_{i,t} + \beta_2 \text{Size}_{i,t} + \beta_3 \frac{\text{Debt}}{\text{EBITDA}}_{i,t} + \beta_4 \frac{\text{Cash}}{\text{Asset}}_{i,t} + \beta_5 \text{Age}_{i,t} + \beta_6 \text{MM}_{i,t} + \gamma_{\text{year}} + \delta_{\text{sector}}\Bigg) \quad (2)$$

In selecting our covariates, we follow previous literature by incorporating key financial metrics (refer to, e.g., Chan-Lau, 2006). We include net income over assets as a *profitability ratio*, the logarithm of total assets as a proxy for *firm size*, debt over EBITDA as a *leverage ratio*, cash over assets as a *liquidity ratio*, and firms' age. Additionally, we include the *measure of maturity mismatch* (MM), defined as current liability minus cash divided by total liabilities. We also include year and sector (defined by the first two-digit NAICS code) fixed effects to account for variations in the probability of default over time, such as during periods like the financial crisis, as well as across different sectors.

Figure 3 shows the normal distributions of the estimated probability of distress (Altman Z-score below 1.8) and probability of default for bankrupted firms with green and brown business descriptions in the year before default. The results indicate that firms with brown business descriptions have a higher probability of distress and default compared

[8]The Altman Z-Score was initially designed for large public companies. To ensure the robustness of our findings, we conducted additional analyses using the Altman Z'-Score and Altman Z"-Score. See table B1 for details of the variables used.

Figure 3: Normal distributions of estimated default and distress probabilities.



(a) Probability of distress

(b) Probability of default

Note: This figure shows the normal distributions of the estimated probability of distress (Figure a) and the probability of default (Figure b) for bankrupted firms in the year before default. The normal distributions are plotted for firms with brown business descriptions and those with green business descriptions. The mean and standard deviation of the estimated probabilities are used to generate these distributions for each group.

to those with green business descriptions. The last column in Figure A7(a) and (b) in the Appendix further confirms that these estimated probabilities are statistically different for both bankrupted and non-bankrupted companies.

We also examine additional climate risk proxies, such as sector classification and carbon emissions. For non-bankrupted companies, Figure A7(a) shows that "brown" firms, in terms of absolute emissions, are on average more likely to face financial distress and exhibit a higher probability of default. However, when categorizing by climate sector, we find that firms in "brown" sectors are less likely to experience distress but have a higher likelihood of bankruptcy.

When analyzing firms prior to default, Figure A7(b) demonstrates that large emitters are more prone to financial distress, though there is no significant impact on their probability of default. We also find no significant effect from sector classification. This suggests that sector classification may not fully capture the diversity of firms' climate risks, while emissions align more closely with our business description findings.[9] [10]

[9] Since the sample of brown firms is larger than that of green firms, the figures in A8 use propensity score matching (based on size, debt-to-EBITDA, age, and matching within a given year and sector) for green and brown firms. The results are consistent.

[10] In the Appendix, Figure A13 replicates these findings using the S&P dataset. Although the S&P dataset lacks several fundamental variables such as leverage, working capital, and sales (which are proxied by other variables), the results are remarkably similar to those from the Orbis dataset.

Overall, our initial analysis suggests that climate risk significantly impacts the likelihood of financial distress and appears to influence the probability of corporate bankruptcies.

4.2 Do Climate Risks Impact the Type and Cost of Bankruptcy?

In this section, we investigate whether green and brown firms incur different bankruptcy costs. Firstly, we assess whether companies that are defined as green are more likely to liquidate rather than restructure, our hypothesis is bi-fold: i) creditors have the belief that green companies are riskier, as they enter new markets and face uncertain demand, or ii) creditors internalise climate transition costs and forecast brown companies to be less profitable than green companies in the future. Secondly, we investigate whether firms face different bankruptcy costs, represented by the length of the bankruptcy process.

Liquidate or Reorganise? To assess whether brown companies are more likely to file for liquidation or reorganisation, we use the following probit model:

$$\Pr(\text{Reorganise}_{bt} = 1) = \Phi\Big(\beta_0 + \beta_1 \cdot 1(\text{Climate Indicator})_b + \beta_2 \cdot Z_b + \delta_T + \gamma_S\Big) + \epsilon_{bt} \quad (3)$$

The variable $1(Reorganise)_{b,t}$ takes the value of 1 if the bankrupted company b files for Chapter 11 (reorganisation) and 0 if it files for Chapter 7 (liquidation) in a given year t. The variable $1(ClimateIndicator)_b$ is a binary variable that takes the value of 0 if the company is neutral (i.e., its business description does not include any green or brown terminology) and 1 if the company is green (in columns 1-4) or brown (in columns 5-8). The vector Z includes firm-level control variables, specifically firm size (total assets) and leverage (total liabilities). The fixed effects δ_T and γ_S represent coefficient vectors for the year and the court state of bankruptcy filing, respectively.

Table 2 shows that brown firms are more likely to reorganize compared to their neutral counterparts, with their coefficients remaining positive and statistically significant even after controlling for size, leverage, and including court-district and year-fixed effects. In contrast, the results for green firms are less clear. Without controls, green firms also appear more likely to reorganize; however, when adjusting for size and leverage, the coefficient reverses, suggesting they are more likely to liquidate. This ambiguity limits our ability to draw firm conclusions about the reorganization likelihood for green firms.

Table 2: Bankruptcy filing by firm's climate classification

	Reorganise							
	Green				**Brown**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Indicator	0.057*	-0.108*	0.050*	-0.113*	0.471***	0.191**	0.394***	0.180*
	(0.028)	(0.062)	(0.029)	(0.064)	(0.027)	(0.059)	(0.028)	(0.061)
Size and Leverage (bins) controls		X		X		X		X
Court District and Year FE			X	X			X	X
Pseudo R^2	0.010	0.414	0.223	0.5625	0.010	0.339	0.115	0.431
N	39,144	8,066	39,144	8,066	39,455	8,329	39,455	8,329

Note: The regression reports the likelihood of companies filing for Chapter 11 if they are green (columns 1-4) or brown (columns 5-8) over a control group of neutral firms. The controls are firm size and leverage bins constructed from the bankruptcy dataset. It also includes District and Year Fixed Effects. The standard errors are clustered at the court district level.

Cost of Bankruptcy We investigate how climate risk affects the cost of bankruptcy. Following Bris et al. (2006), we use the length of the bankruptcy process as a proxy for bankruptcy cost. Our key specification is as follows:

$$\log(\text{process length in days})_{bt} = \beta_0 + \beta_1 * 1(\text{Climate Indicator})_b + \beta_2 * Z_b + \delta_T + \gamma_S + \epsilon_{bt} \quad (4)$$

The dependent variable is the cost of bankruptcy, which can be influenced by the assigned judge as well as by the complexity of the case and the creditors' landscape. The length of the bankruptcy process is measured in days, from the filing date to the date the case is closed or resolved. The main independent variable is the previously described $ClimateIndicator$. We also control for bins of firm size (total assets) and leverage (total liabilities) constructed in BD and we include year and court district fixed effects.

Table 3 regression outcomes suggest a notable trend: brown firms appear to have shorter bankruptcy processes when compared to their neutral counterparts. This effect is statistically significant in models that include court district and year-fixed effects, indicating a robust association between the environmental classification of brown firms and a reduced duration of bankruptcy procedures. On the contrary, green firms do not show a statistically significant difference in bankruptcy length. Notice that the sample used for this section is smaller than what has been used in table 2 due to lower data availability for the Federal Judicial Center dataset. For consistency, we have replicated regression 3 with the same sample as this section (table B3 in the appendix) and we obtain similar results for brown firms, albeit slightly less significant.

Table 3: Bankruptcy length by firm's climate classification

	Log(Process length in days)							
	Green				**Brown**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate indicator	0.067	0.038	−0.060	−0.100	−0.037	−0.200*	−0.177*	−0.283**
	(0.135)	(0.131)	(0.122)	(0.119)	(0.101)	(0.102)	(0.095)	(0.171)
Size and Leverage (bins) controls		X		X		X		X
Court District and Year FE			X	X			X	X
R^2	0.0002	0.074	0.278	0.324	0.0002	0.055	0.276	0.309
Adj. R^2	-0.001	0.072	0.231	0.277	-0.001	0.052	0.232	0.265
N	980	962	921	903	1,023	1,004	965	945

Note: The regression reports the difference in log(process length in days) for green firms (columns 1-4) and brown firms (columns 5-8) over a control group of neutral firms. The controls are firm size and leverage bins constructed from the bankruptcy dataset. It also includes the court's district and year-fixed effect. The standard errors are clustered at the court district level.

5 Post-Bankruptcy Facility Emissions

In this section, we examine how bankruptcy impacts the environmental performance of facilities whose firms have filed for bankruptcy. Our primary focus is on the emissions from these facilities, particularly comparing the outcomes following whether they are assigned to a more lenient or stricter judge).

5.1 Identification Strategy

Studying post-bankruptcy asset utilization is challenging due to selection bias in bankruptcy filings. Firms that choose Chapter 7 may have lower forecasted cash flows and management issues, affecting their post-bankruptcy environmental and managerial performance. To address this bias, we leverage the random assignment of judges, similar to Aloisio et al. (2023).

Our methodology takes advantage of the random assignment of cases to judges with varying degrees of pro-continuation bias. In the U.S. bankruptcy system, judges have the authority to convert cases between Chapter 7 and Chapter 11 based on the circumstances. This flexibility allows the process to adapt, maximizing value for creditors (Warren, 2003). Since bankruptcy cases are randomly assigned to judges within a district, firms cannot choose their judge, making the degree of continuation bias they encounter independent of their initial characteristics.

We construct judges' pro-continuation bias based on the probability of continuation for firms assigned to a given judge. Specifically, we develop a leave-one-out measure of the

continuation bias faced by a bankrupt firm b assigned to judge j in judicial district d.

$$M_{bjd} = \frac{1}{N_{jd} - 1} \sum_{b' \neq b} C_{b'jd} \tag{5}$$

N_{jd} is the total number of cases assigned to judge j in judicial district d, and $C_{b'jd}$ is an indicator function equal to one if bankrupt firm b' continues in operation five years after bankruptcy, and 0 if not. For each bankrupt firm b, this measure captures the average continuation after bankruptcy, computed using all other firms assigned to the same judge. Given the limited number of bankruptcy cases matched with facilities available for different judges in our sample, the exclusion of the bankrupt firm b's continuation outcome avoids the finite-sample bias resulting from the mechanical correlation between $C_{b'jd}$ and the measure of continuation bias. We focus on districts with at least two judges which in turn had at least 10 bankruptcy cases filed during the period under study.

Figure 4 shows the distribution of pro-continuation bias across court districts, focusing only on those districts where we have a facility from a bankrupt firm. The figure highlights substantial heterogeneity in continuation within our sample, with lower values indicating a lower probability that firms will remain operational five years post-default. In the Appendix, Figure A6 presents the geographical variation in pro-continuation bias across and within U.S. court districts, again focusing only on districts where we have a facility. The map averages pro-continuation bias at the state level. The box plot shows the range of pro-continuation bias values in each court district of our sample, documenting both the lowest and highest values.

Our main empirical specification, similar to Aloisio et al. (2023), is as follows:

$$\text{Log(Emissions)}^{T}_{pbjd} = \beta M_{bjd} + \gamma X_{pbjd,t-1} + FE + \epsilon_{pbjd} \tag{6}$$

$\text{Emissions}^{T}_{pbjd}$ represents the emissions of plant p belonging to a bankrupt company b from the year of bankruptcy up to two years post-bankruptcy, for a case assigned to judge j in district d during bankruptcy year t. Our main coefficient of interest is β, which captures the effect of pro-continuation bias on plant-level emissions in the post-bankruptcy period.

In all regressions, standard errors are clustered at the court division level to account

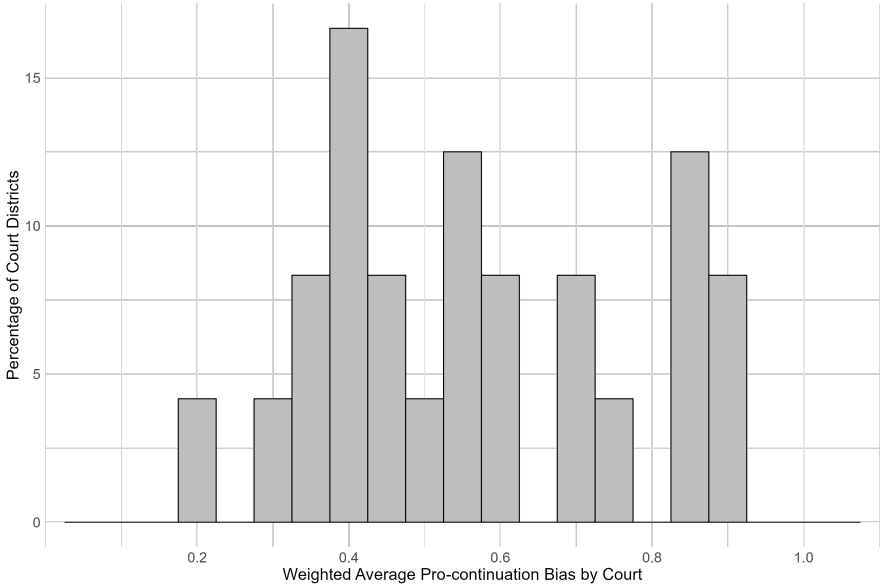


Figure 4: Distribution of Pro-continuation Bias across Districts.

Note: The histogram shows the percentage of court districts in our sample that are associated with facilities where the firm went bankrupt, categorized by the court's pro-continuation bias. A judge's pro-continuation bias is calculated as the proportion of firms that remain operational five years post-bankruptcy, relative to all firms overseen by that judge. To aggregate this variable at the court district level, we weight each judge's continuation bias by the number of cases they have handled.

for any within-court correlation. $X_{pbjd,t-1}$ includes firm-level controls, such as revenue, assets, liabilities, and employment, derived from bankruptcy data and reported in bins, as well as plant emissions from the year prior to bankruptcy.

We also include several fixed effects (FE). Specifically, we control for judicial-district fixed effects interacted with year of emission to compare companies that file in the same district and the same post-year. Additionally, we include sector fixed effects to account for sector specific characteristics. Furthermore, we incorporate judicial-district fixed effects interacted with bankruptcy-year fixed effects to ensure that the variation stems from differences across plants whose companies file for bankruptcy in the same judicial district and time but are randomly assigned to judges with varying levels of pro-continuation bias.

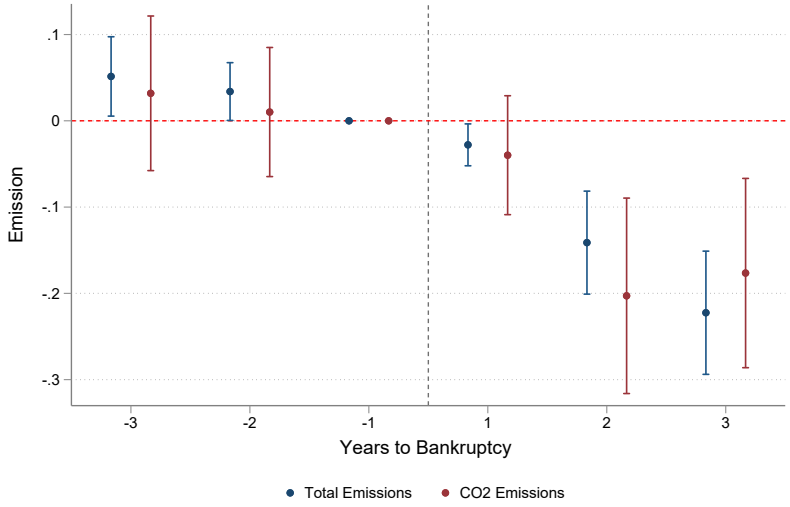
5.2 Empirical Results

We begin by examining how total emissions and total CO2 emissions change at the facility level around the time of bankruptcy. Figure 5 illustrates that both total emissions and total CO2 decrease after bankruptcy, becoming statistically significant within

2 years following the filing of a bankruptcy case. While the main analysis focuses on total facility emissions, we include carbon emission results in the appendix for robustness.

We leverage the random assignment of judges to examine whether different types of bankruptcy affect facility emissions. Table 4 presents the results of equation 6 examining the impact of judges' continuation bias on log-transformed total emissions for plants of bankrupted firms from the year of bankruptcy to two years after. Continuation bias is negatively associated with log(Total Emission), indicating that higher levels of continuation bias in bankruptcy courts are associated with lower emission levels post-bankruptcy.

Figure 5: Facilities emissions around the year of bankruptcy.



Note: The graph plots the change in total and CO2 emissions around bankruptcy, where 1 is the bankruptcy year. The regressions include sector and district*year fixed effects. The standard errors are clustered at the facility level. Confidence intervals are shown at 90% level.

The results suggest that firms subjected to judges with a higher tendency towards reorganization rather than liquidation might adopt practices that lead to reduced emissions. This result is consistent when introducing firm-level controls of firms' fundamentals (in bins) and lagged emissions. The R-squared values increase substantially from column (1) to column (6), indicating an improvement in the model's explanatory power, particularly with the addition of lagged emissions. Similar results are reported in the analysis of carbon emissions, as shown in Table B5 in the Appendix.

Table 4: Results of the OLS Regression for Total Emissions

	log(Total Emission)					
	(1)	(2)	(3)	(4)	(5)	(6)
Continuation Bias	-1.840*	-4.153***	-3.111***	-2.990***	-1.636***	-0.318**
	(1.003)	(1.024)	(0.487)	(0.467)	(0.294)	(0.119)
Asset (bins)		0.134	-0.0750*	-0.105*	-0.138**	-0.0375
		(0.162)	(0.0393)	(0.0463)	(0.0503)	(0.0239)
Revenue (bins)		-0.137**	-0.174**	-0.115***	-0.147***	-0.0283*
		(0.0534)	(0.0676)	(0.0187)	(0.0161)	(0.0128)
Liabilities (bins)		0.0778	0.232**	0.186**	0.175**	0.0174
		(0.132)	(0.0852)	(0.0556)	(0.0711)	(0.0143)
Employment (bins)		-0.0262***	-0.0304**	-0.0111	0.000324	0.00275
		(0.00692)	(0.0108)	(0.00724)	(0.0106)	(0.00776)
$log(TotalEmission)_{t-1}$						0.989***
						(0.0288)
District*Year FE			X	X		X
Sector FE				X	X	X
District*Bankruptcy Year FE					X	
R^2	0.0417	0.197	0.314	0.377	0.411	0.894
Adj. R^2	0.0410	0.193	0.282	0.345	0.389	0.888
N	1302	954	932	932	954	932

Note: The regression reports the facility's total emissions from the year of the bankruptcy filing to two years after. For companies that sold the facility the year before the filing, we include that year and the two following years. Continuation bias is based on the probability of continuation after the bankruptcy of firms assigned to a given judge. The controls are bins of revenue, assets, liabilities, and employment constructed from the bankruptcy dataset. We also control for the log of total emissions in the year before filing for bankruptcy. The fixed effects are NAICS sector fixed effects, court district interacted with emission year, and court district interacted with bankruptcy year. The decrease in the number of observations is because 116 out of 434 facilities are missing at least one control variable. The standard errors are clustered at the court district level.

5.3 Mechanisms

This section explores the potential mechanisms through which post-bankruptcy companies might increase their environmental performance. Three main mechanisms are considered: debt relief, asset specificity, and under-utilisation of facilities.

Debt Relief. One potential mechanism is debt relief. Post-bankruptcy companies often have significantly lower debt burdens, which can free up financial resources that can be re-invested into more sustainable and environmentally friendly practices. According to Hartzmark and Shue (2023), without appropriate financing brown firms cannot improve their environmental performance, similarly Aymeric Bellon (2024) find that firms increase their pollution intensity as they become more financially distressed. The reduction in debt obligations allows companies to allocate a greater portion of their profits towards green investments. This financial flexibility can enable firms to upgrade to more energy-efficient technologies, reduce waste, and lower their overall environmental footprint.

Asset Specificity. In this section we hypothesize that after a liquidation, when a factory changes ownership, the latter might operates less efficiently due to the misalignment of transaction-specific assets with the new owner's needs. This finding would be aligned with transaction cost theory (Williamson, 1981), highlighting that transactions are most efficiently governed when their unique attributes align with the governance structures that minimize associated costs. In this context, transaction-specific assets, which are highly tailored to a specific transaction and difficult to redeploy outside the original relationship, become a key challenge. With respect to the bankruptcy process, Kermani and Ma (2022) find that the liquidation value of fixed assets is 35% of the net book value in the average industry, this results highlights how nonfinancial firms have high asset specificity. Following this literature we hypothesize that, after a bankruptcy, the loss of this alignment between transaction attributes and governance structures results in inefficiencies, as the new ownership may lack the specific capabilities or organizational alignment to fully utilize the factory's tailored assets.

Specifically in manufacturing and industrial facilities, asset specificity is high due to specialized machinery and tailored production processes (Besanko et al., 2000). For example, equipment designed for a specific product is often costly to repurpose, creating hold-up problems if the original production context is changed (Klein et al., 1978).

New owners may struggle to manage these specialized assets effectively, resulting in inefficiencies.

Empirical studies, such as Bernstein et al. (2019), show that firms retaining their original ownership post-restructuring tend to perform better than those undergoing liquidation and ownership changes. Original owners better understand and leverage asset specificity, while new owners often face challenges adapting these assets, leading to reduced performance and poorer environmental outcomes due to less efficient management and lower investment in facility-specific technologies.

Under-utilisation of Facilities. After a bankruptcy filing, many industrial facilities might experience a significant reduction in their operational capacity. This underutilization often occurs as firms face financial constraints that limit their ability to maintain or increase production levels. Consequently, these facilities may not operate at their full potential, leading to a lower output of goods and services. The reduced industrial activity is often accompanied by a decline in resource consumption and energy usage, which can result in lower emissions. In particular, facilities that were previously major contributors to local pollution may emit less greenhouse gases and other pollutants simply because they are producing less. This phenomenon reflects the broader economic impact of bankruptcy, where struggling firms are unable to invest in or optimize their production processes (White, 2001; Allcott and Greenstone, 2012).

However, this reduction in emissions is not necessarily indicative of improved environmental practices or technological advancements. Instead, it is a byproduct of financial distress and the consequent scaling back of operations. While lower emissions from underutilized facilities might temporarily benefit the environment, this situation could also lead to inefficiencies and waste of industrial resources. Moreover, if the firm eventually recovers or if the facility is acquired by another entity, production levels—and thus emissions—could rise again. Therefore, while the immediate aftermath of bankruptcy might show a decline in emissions, this effect may be temporary and does not necessarily contribute to long-term environmental sustainability (Graham et al., 2005).

Results. We begin to test whether debt actually decrease following the bankruptcy filing. To do so, we collect debt information of the companies which filed for Chapter 11 from Orbis and implement a panel event study methodology, in line with de Chaisemartin and D'Haultfœuille (2020), where our sample is composed by companies that

will eventually file for bankruptcy.[11] We then assess whether companies identified as brown reduce their debt more than green and neutral companies.

Table 5: Bankruptcy impact on debt

Sample	Full Sample	Brown, Green and Neutral Companies	Brown and Green Companies
Dependent Variable: Log Debt	(1)	(2)	(3)
Post Event	-0.105*	-0.006	0.025
	(0.045)	(0.048)	(0.109)
Post Event * Brown Company		-0.244**	-0.299*
		(0.078)	(0.122)
Controls (Sector and Total Assets)	X	X	X
District * Year FE	X	X	X
Adj. R^2	0.909	0.905	0.937
N	2,836	2,020	707

The regression examines changes in company debt five years before and after a Chapter 11 bankruptcy. Column 1 uses the full sample of available debt data, while Column 2 focuses on the sample of all companies with climate classification based on Giannetti et al. (2023) (categorized as brown, green, and neutral). Column 3 includes only brown and green companies. In Column 2, green and neutral companies serve as the control group, while in Column 3, only green companies form the control group (in both cases, brown companies constitute the treatment group). Consistent with previous empirical specifications, the model includes fixed effects for sector (NAICS Group), district, and year. Additionally, we control for total assets, using the logarithm of total assets as a control variable to align it with the dependent variable.

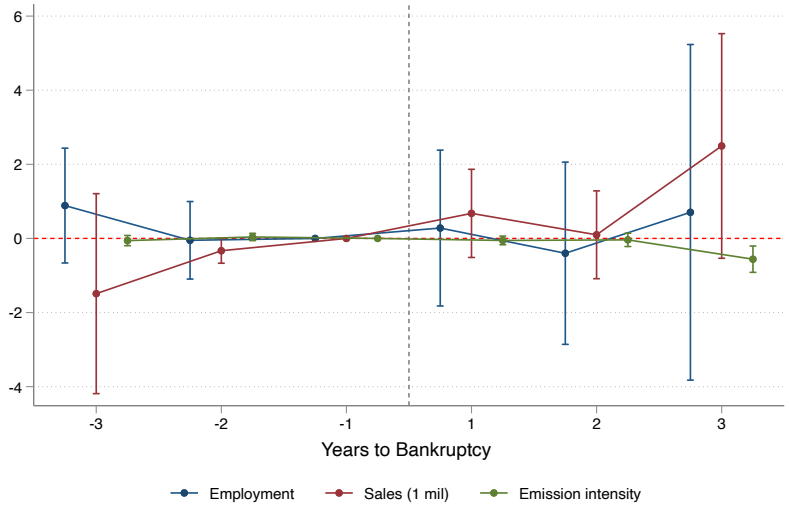
Table 5 shows the change in debt following bankruptcy across three different samples, in the full sample companies reduce their debt following a Chapter 11 bankruptcy. Column 2 and 3 show that brown companies experience a more pronounced reduction in debt compared to green and neutral companies, confirming our hypothesis that brown companies might receive a greater reduction of debt which could help them to become greener following the bankruptcy. We include total assets as a control variable to account for differences in company size, which can influence both the ability to carry debt and the magnitude of debt reduction during bankruptcy. We use the logarithm of total assets to align with the dependent variable, ensuring comparability and reducing issues of scale.

Next, we test for asset utilization by analyzing carbon intensity, employment, and sales during the bankruptcy period. For this analysis, we merge facilities from our EPA-BD dataset with NETS establishments, which provides additional information on employment, sales, repayment scores, and repayment risks. Figure 6 displays the dynamic changes in facility employment, sales, and carbon intensity surrounding bankruptcy. The results indicate no significant changes in employment or sales, while emission inten-

[11] We use the broad terminology of debt to classify the sum of current liabilities and long term liabilities.

sity significantly decreases after the third year, consistent with a reduction in absolute emissions.

Figure 6: Dynamic changes in employment, sales and carbon intensity.



Note: This figure illustrates the difference in facility employment, sales and carbon intensity 3 years before and after bankruptcy. The regression includes industry and court district-year FE. The standard error are clustered at the facility level. The confidence intervals are at the 90 confidence level.

Table 6: Results of the OLS Regression for the Mechanisms

Dependent variable:	(1) log(CO2 emiss/sales)	(2) log(tot emiss/sales)	(3) Sales	(4) Employees	(5) Repayment Score	(6) Repayment Risk
Continuation Bias	-9.978**	-9.714***	19.38	18.64	14.51**	-23.06**
	(2.618)	(1.077)	(116.4)	(30.35)	(4.861)	(8.032)
Controls FE	X	X	X	X	X	X
District*Year FE	X	X	X	X	X	X
R^2	0.408	0.215	0.250	0.245	0.166	0.285
Adj. R^2	0.343	0.143	0.183	0.177	0.00404	0.146
N	224	309	315	315	124	124

Note: The regression reports the facility's emission intensity, as total emissions and carbon emission, as well as employment, sales, repayment score and risk from the year of the bankruptcy filing to two years after. Repayment score, ranging from 1 to 100, which indicates the likelihood of a facility repaying its debts. Repayment risk, defined as the difference between the minimum and maximum score within a month, reflects the certainty of the repayment score. Continuation bias is based on the probability of continuation after the bankruptcy of firms assigned to a given judge. The controls are bins of assets, liabilities, and employment constructed from the bankruptcy dataset. The fixed effects are court district interacted with emission year. The decrease in the number of observations is because 116 out of 434 facilities are missing at least one control variable. The standard errors are clustered at the court district level.

We corroborate the findings of Figure 6 by regressing judge continuation bias on our variables of interest. Table 6 aligns with our results, indicating that firms facing more

lenient judges have lower carbon intensity, whether measured as total emissions or carbon emissions. We also find no significant effects on sales or employment, suggesting that these changes are not driven by labor or production adjustments.

For a small subset of companies, we have a repayment score ranging from 1 to 100, which indicates the likelihood of a facility repaying its debts. Repayment risk, defined as the difference between the minimum and maximum score within a month, reflects the certainty of the repayment score. Note that these firms are predominantly those that have undergone reorganization, resulting in a highly selective sample. Consistent with previous findings regarding debt levels at the company level, we observe that facilities exhibit higher repayment scores and lower repayment risk, indicating reduced financial constraints.

Overall, the results indicate a debt mechanism at play. While asset specificity cannot be entirely ruled out, the evidence suggests that debt reduction, observed at both the company and facility levels, is at least partially responsible for the observed outcomes.

5.4 Robustness tests

In this section, we address potential sample selection issues that may bias our results. First, we examine whether we may have excluded facilities that, post-bankruptcy, reduced their emissions and therefore stopped reporting to the EPA. Figure A10 plots the number (a) and share (b) of facilities that stopped reporting to the EPA with respect to their bankruptcy year. We observe that almost 30% of the sample does not have reporting data after three years. However, this is mainly because these bankruptcies occurred in 2019, and the last year available in our sample is 2022. Therefore, this is driven by data availability rather than a lack of sample.

Second, we might be concerned that there is a significant number of facilities sold around the time of bankruptcy, which could hinder our results. Note that in our main sample, we also include facilities that were sold in the year before bankruptcy, however, these are only 9% of the sample. Figure A11 plots the change in the number of facilities (blue) and the year-on-year change around bankruptcy (red). The regression controls for parent company ID fixed effects. We find no statistical significance for either variable, suggesting that our results are not driven by facilities changing ownership around default.

6 Conclusion

We explore the intersection between climate risks and corporate bankruptcy. By linking corporate bankruptcies with environmental indicators over a period from 2000 to 2023, we show that brown companies are more vulnerable to financial distress and, subsequently, to bankruptcy.

We also show that post-bankruptcy, firms tend to exhibit a decrease in emissions, particularly when they are assigned to more lenient judges. Our analysis leverages the random assignment of bankruptcy judges to address the endogeneity concerns related to bankruptcy decisions. We show that judicial bias towards reorganization leads to significantly lower post-bankruptcy emissions. Underscoring the role of judicial discretion in shaping not only the financial outcomes of bankruptcy but also its environmental impact.

We propose three potential mechanisms to explain why reorganized firms tend to have better environmental outcomes: debt relief, asset specificity, and facility under-utilization. Our findings do not support under-utilization as the primary mechanism, given the lack of significant changes in sales and employment. Instead, the evidence points towards a combination of debt reduction and the preservation of asset specificity as key factors.

The implications are twofold. First, we contribute to the broader discourse on the economic impacts of climate change by demonstrating how financial distress and bankruptcy can influence environmental performance. Second, they highlight the importance of considering environmental factors in bankruptcy proceedings. The ability of reorganization to improve environmental outcomes suggests that policymakers and practitioners could integrate sustainability considerations into the bankruptcy process.

In conclusion, by showing that reorganization can lead to better environmental outcomes, our findings suggest that bankruptcy processes, traditionally focused on financial recovery, could also play a role in advancing sustainability goals.

References

Aghion, P., Hart, O., and Moore, J. (1992). The economics of bankruptcy reform. *Journal of Law, Economics, & Organization*, 8(3):523–546.

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives*, 26(1):3–28.

Aloisio, A., Ferreira, R., Lagaras, S., Moraes, F., Ponticelli, J., and Tsoutsoura, M. (2023). The labor effects of judicial bias in bankruptcy. *Journal of Financial Economics*, 150(2).

Altman, E. I. (2013). 17 predicting financial distress of companies: revisiting the z-score and zeta® models1. *Handbook of research methods and applications in empirical finance*, page 428.

Aymeric Bellon, Y. B. (2024). Pollution-shifting vs. downscaling: How financial distress affects the green transition. *Available at SSRN 4761314*.

Baird, D. G. (1986). The uneasy case for corporate reorganizations. *The Journal of Legal Studies*, 15(1):127–147.

Baird, D. G. (2020). *The Elements of Bankruptcy*. Foundation Press.

Bernstein, S., Colonnelli, E., and Iverson, B. (2019). Asset allocation in bankruptcy. *The Journal of Finance*, 74(1):5–53.

Besanko, D., Dranove, D., Shanley, M., and Schaefer, S. (2000). *Economics of Strategy*. John Wiley & Sons.

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

Bris, A., Welch, I., and Zhu, N. (2006). The costs of bankruptcy: Chapter 7 liquidation versus chapter 11 reorganization. *The journal of finance*, 61(3):1253–1303.

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. Technical report, ECB Working Paper.

Chan-Lau, J. A. (2006). Fundamentals-based estimation of default probabilities: a survey. *IMF Working Paper No. 2006/149*.

Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.

Colmer, J., Martin, R., Muûls, M., and Wagner, U. J. (2024). Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading System. *The Review of Economic Studies*, page rdae055.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Faralli, M. and Ruggiero, F. (2022). The rise of climate risks: Evidence on firms' expected default frequencies. *Available at SSRN 4144802*.

Giannetti, M., Jasova, M., Loumioti, M., and Mendicino, C. (2023). "glossy green" banks: The disconnect between environmental disclosures and lending activities.

Graham, J. R., Harvey, C. R., and Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of accounting and economics*, 40(1-3):3–73.

Hartzmark, S. M. and Shue, K. (2023). Counterproductive impact investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

Hotchkiss, E. S. (1995). Postbankruptcy performance and management turnover. *The Journal of Finance*, 50(1):3–21.

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

Ivashina, V., Iverson, B., and Smith, D. C. (2016). The ownership and trading of debt claims in chapter 11 restructurings. *Journal of Financial Economics*, 119(2):316–335.

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.

Kacperczyk, M. T. and Peydro, J.-L. (2024). Carbon Emissions and the Bank-Lending Channel. *European Corporate Governance Institute – Finance Working Paper*, page No. 991/2024.

Kermani, A. and Ma, Y. (2022). Asset Specificity of Nonfinancial Firms. *The Quarterly Journal of Economics*, 138(1):205–264.

Klein, B., Crawford, R. G., and Alchian, A. A. (1978). Vertical integration, appropriable rents, and the competitive contracting process. *The Journal of Law and Economics*, 21(2):297–326.

LoPucki, L. M. (2008). Courting failure: How competition for big cases is corrupting the bankruptcy courts. *University of Michigan Press*.

Pulvino, T. C. (2002). Do asset fire sales exist? an empirical investigation of commercial aircraft transactions. *The Journal of Finance*, 53(3):939–978.

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

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, 47(4):1343–1366.

Strömberg, P. (2000). Conflicts of interest and market illiquidity in bankruptcy auctions: Theory and tests. *The Journal of Finance*, 55(6):2641–2692.

TCFD (2017). Recommendations of the task force on climate-related financial disclosures. *TCFD Report*. Retrieved from https://www.fsb-tcfd.org/publications/final-recommendations-report/.

Thorburn, K. S. (2000). Bankruptcy auctions: costs, debt recovery, and firm survival. *Journal of financial economics*, 58(3):337–368.

Warren, E. (2003). Chapter 11: Reorganizing american businesses. *Aspen Publishers*.

White, M. J. (2001). Bankruptcy and small business. *Regulation*, 24:18.

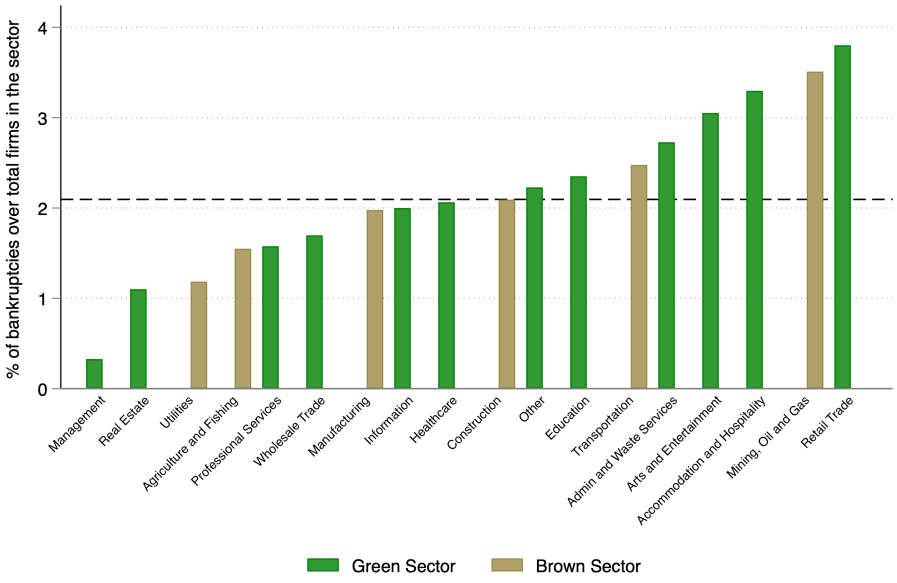
Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American Journal of Sociology*, 87(3):548–577.

Williamson, O. E. (1988). Corporate finance and corporate governance. *The Journal of Finance*, 43(3):567–591.

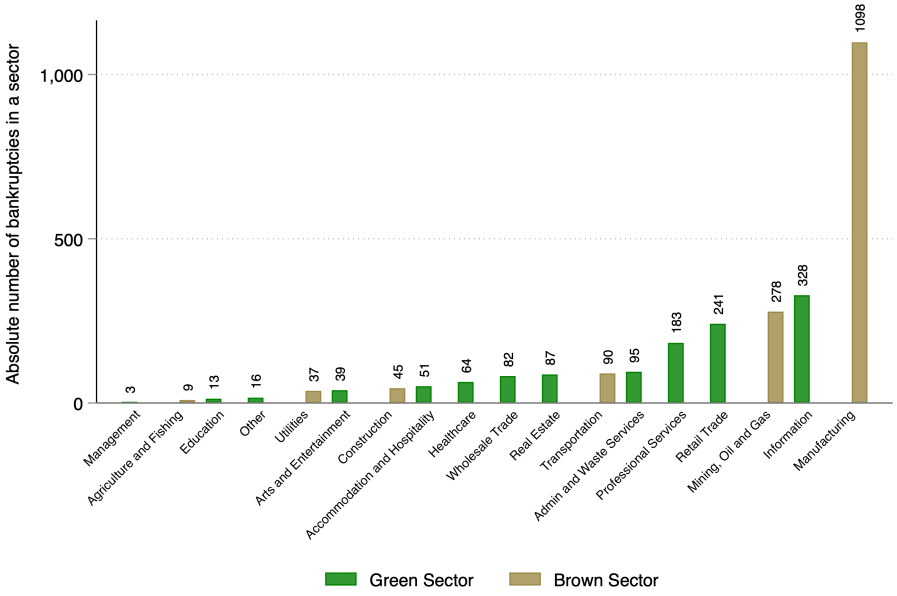
Appendix

A Appendix Figures

Figure A1: Bankruptcies by Sector (Sample 1)



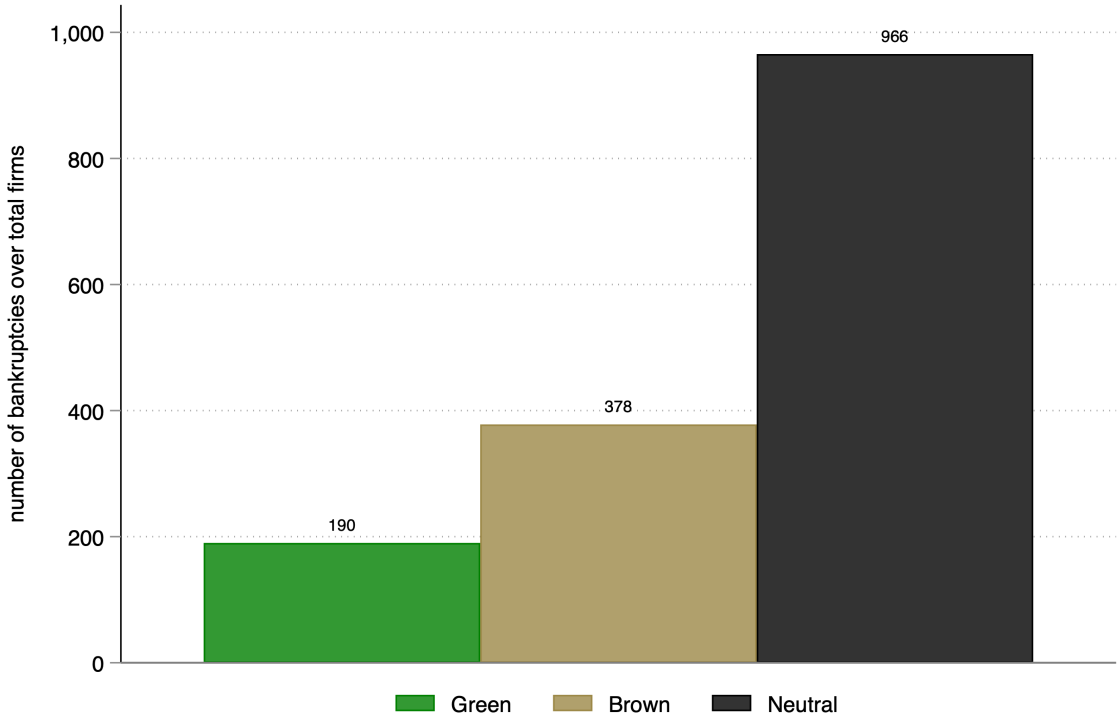
(a) Share of bankruptcies



(b) Total bankruptcies

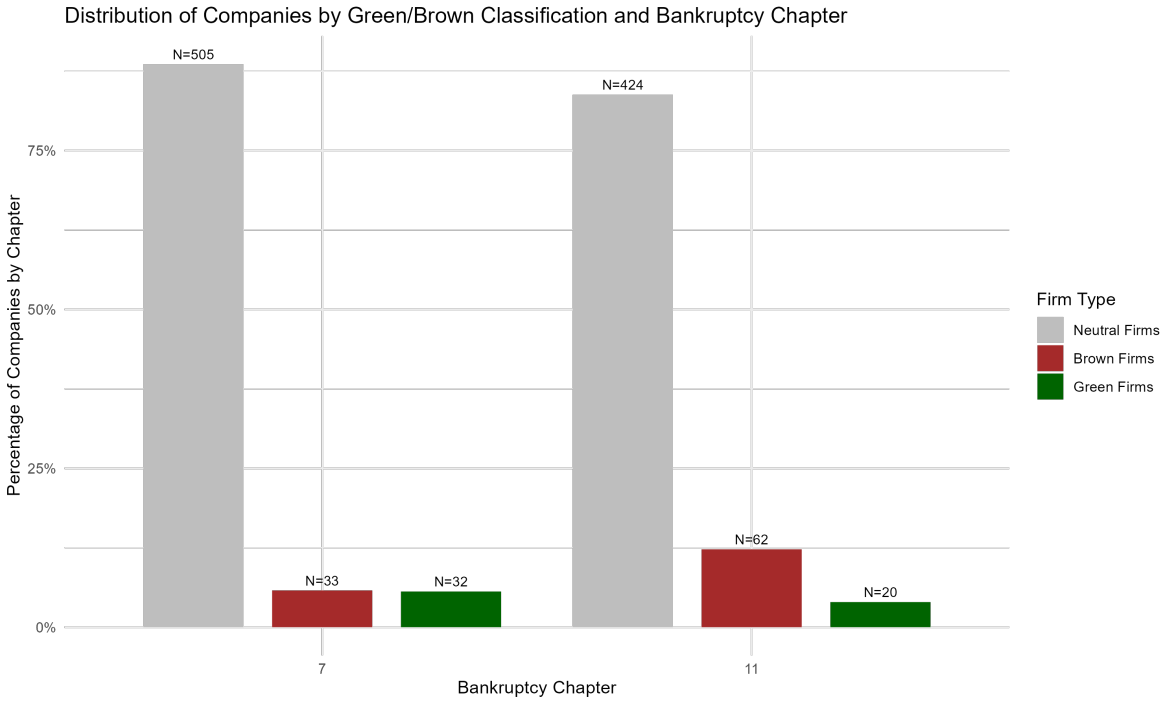
Figure A2: Bankruptcies by Business Description in Orbis (Panel A)

Figure A3: Total bankruptcies



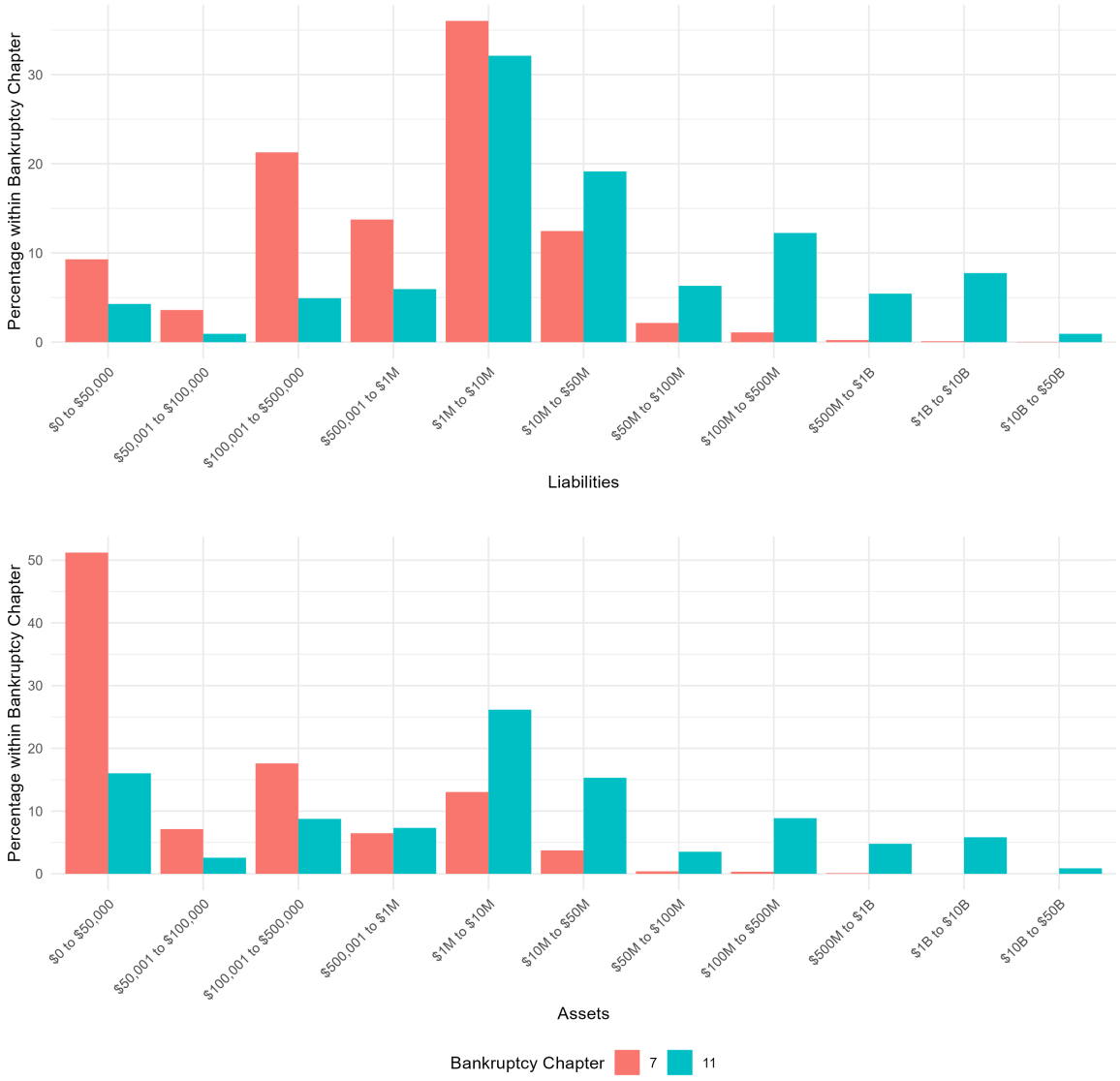
Note: This figure shows the total number of companies by their bankruptcy type and whether based on their business description they are classified as neutral, brown or green firms.

Figure A4: Bankruptcies by Business Description in Length Process (Panel B)



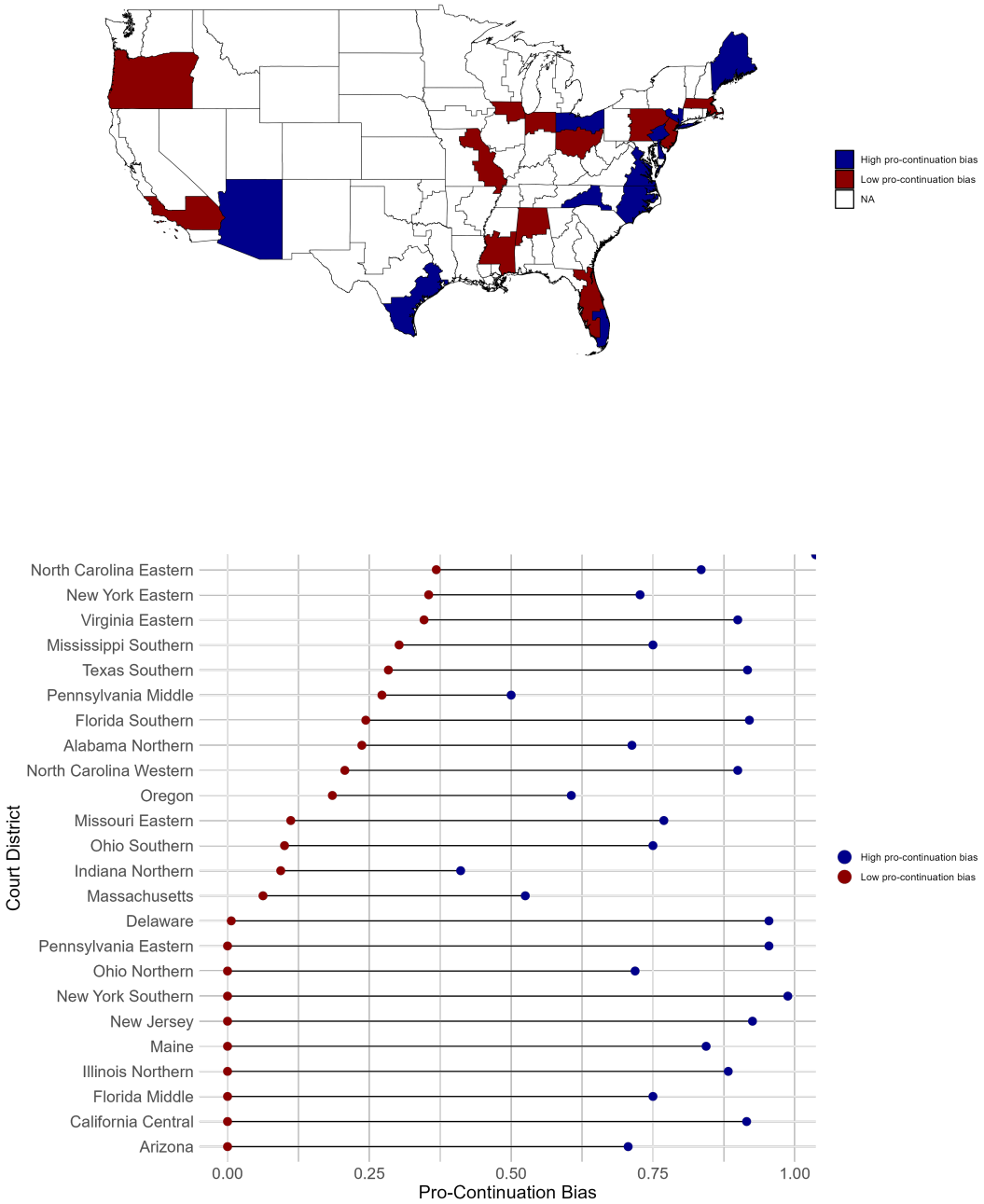
Note: This figure shows the distribution of companies by their bankruptcy type and whether based on their business description they are classified as neutral, brown or green.

Figure A5: Liabilities and Assets of bankrupted companies by filing type (Panel B)



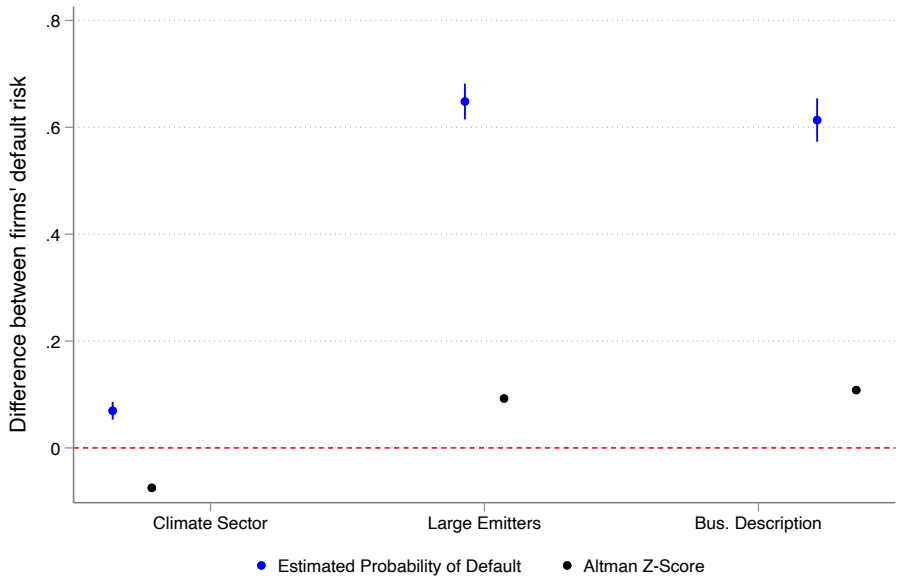
Note: This figure shows the liabilities and assets bins of bankrupted companies by bankruptcy filing type. The choice of ranges is mandated by the fact that liabilities are reported into ranges to the courts when companies file for bankruptcy (the lower bound is inclusive while the upper bound is not, with the exclusion of the largest range).

Figure A6: Pro-continuation bias by Judicial District and Court

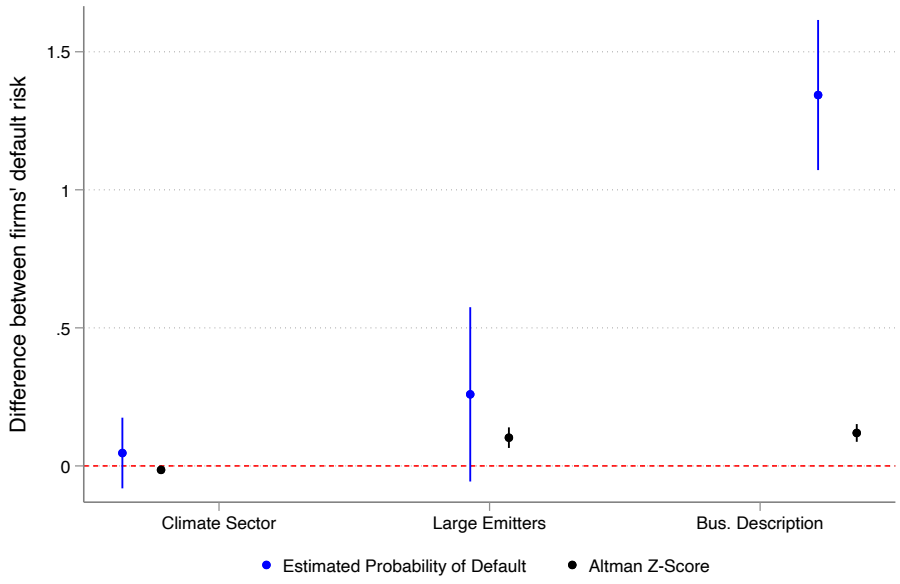


Note: The top figure reports a map with the geographical distribution of our measure of pro-continuation bias across judicial districts where we have a bankruptcy case matched with a facility with emission data. The pro-continuation bias at the judicial-district level is estimated as the weighted average of the bias of the courts present in a judicial district. We classify districts as high vs low pro-continuation-bias districts based on the mean value of the pro-continuation bias measure. The lower part of the figure reports the names of the judicial districts used in the empirical analysis and the range in pro-continuation bias across courts with the red dot representing the lowest pro-continuation bias in the district and blue the highest.

Figure A7: Difference in AZ-Score and Probability Bankruptcy for firms with different climate sensitivity

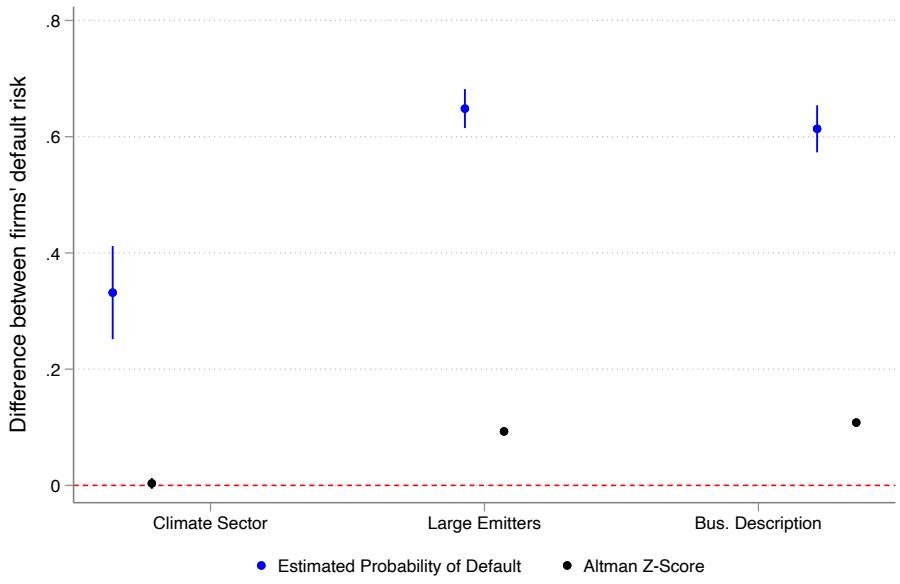


(a) Firms that are not bankrupted

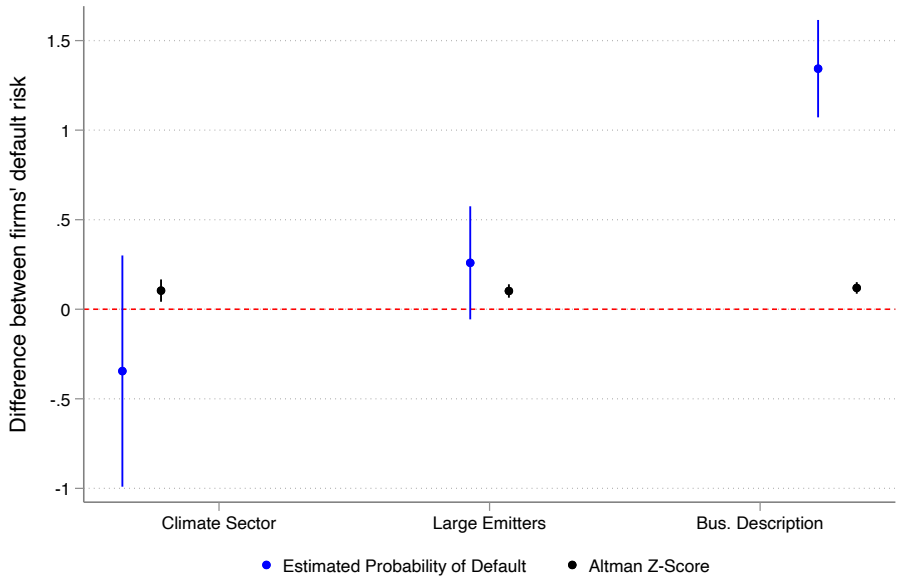


(b) Firms at bankruptcy

Figure A8: Difference in AZ-Score and Probability Bankruptcy for firms (propensity score-matched) with different climate sensitivity

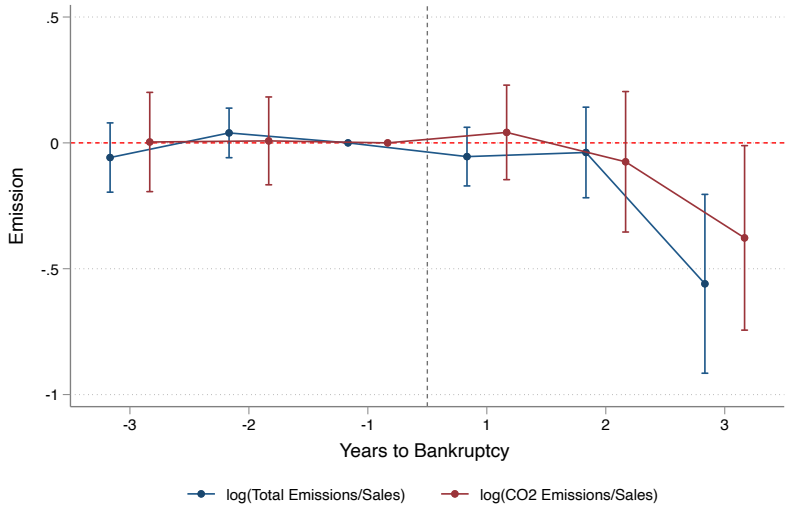


(a) Firms that are not bankrupted



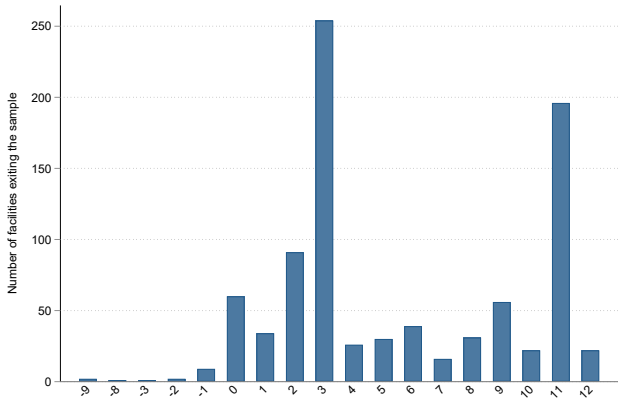
(b) Firms at bankruptcy

Figure A9: Facilities' dynamic changes in Carbon Intensity

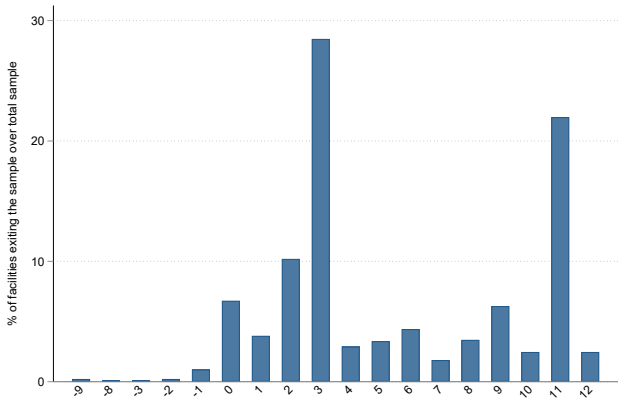


Note: This figure illustrates the proportion of companies that filed for bankruptcies within a specific business description - neutral, green or brown - over the total sample. This ratio is calculated as the number of firms that declared bankruptcy in the matched samples from Orbis and DB, divided by the total number of firms in the Orbis sample. The dashed line indicates the proportion of bankrupted firms in the overall sample.

Figure A10: Facilities exiting the sample by year to bankruptcy



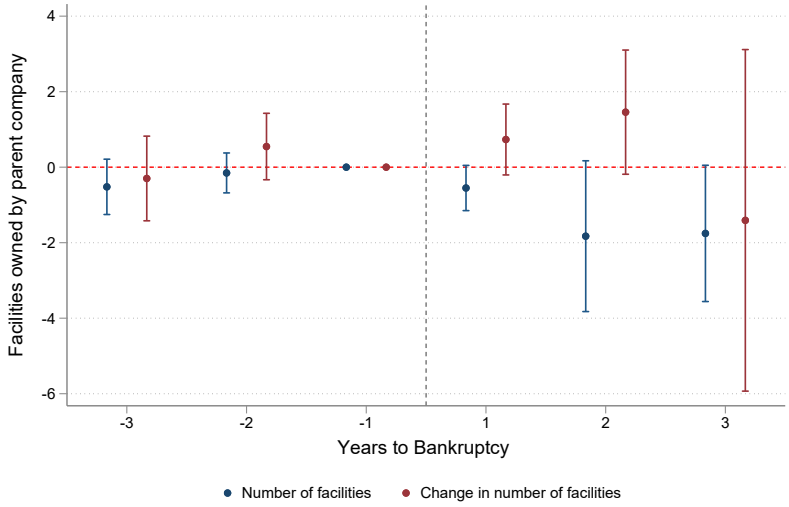
(a) Number of facility



(b) Share over the total sample

This figure plots (a) the number of facilities and (b) the share of facilities at the last year of emission data available, with respect to the bankruptcy year for each facility.

Figure A11: Facility Sales by Parent Company



This figure plots the number of facilities owned by a bankrupted company (blue) and the year-over-year change in the number of facilities (red). The analysts include fixed effects at the parent company and standard errors are clustered at the parent level.

B Appendix Tables

Table B1: Variables description

Variable Name	Description
Panel A: Orbis data with Bankruptcydata	
Total asset	source: total assets (toas) from Orbis
Sales	source: sales (turn) from Orbis
Ebit	source: operating p/l [=ebit] (oppl) from Orbis
Total liabilities	constructed by subtracting shareholders funds (shfd) from total shareholder funds & liab. (tshf), both from Orbis
Working capital	calculated as current assets (cuas) minus current Liabilities (culi) from Orbis
Retained earnings	calculated as stock equity in the previous period - total assets (toas) minus total liabilities minus net common stock (fcsn) - minus profit/loss for the period (net income, pl), and minus total cash dividends paid (fcdp). source: Orbis
Market value of equity	source: shareholders funds (shfd) from Orbis
Firm Size	Logarithm of total assets (toas). Source: Orbis
Debt/Ebitda	Total debt (culi+ltdb) divided by Ebitda (ebta). Source: Orbis
Cash/Total Assets	calculated as cash (cash) divided by total assets (toas). Source: Orbis
Age	calculated as current year minus incorporated year (dateinc year). Source: Orbis
Maturity mismatch (mm)	Current liability (culi) minus cash (cash) divided by total liabilities (tshf - shfd) as a measure of maturity mismatch.
Sector	first 2-digits NAICS code. Source: Orbis
Bus. Desc. Climate Risk	we define brown (green) if its business description in S & P capital IQ contains any brown (green) terminology (from the dictionary provided by Giannetti et al., 2023), neutral if none of them.
Climate Sensitive Sector	follow Choi et al. (2020) that categorized as high climate risk according to the IPCC, which includes agriculture, mining, utilities, construction, manufacturing, transportation, and warehousing, while classifying all other sectors as low climate risk.
High Transition Risk	takes the value 1 if the firm's transition risks are in the top quintile and zero if in the bottom 3 quintiles. Transition risks are proxied by absolute Scope 1 emission from Trucost. To deal with missing values, emissions are averaged across years.
Panel B: Bankruptcydata with FCJ	
Log(Process length in days)	measured in days, from the filing date to the date the case is closed or resolved, and reported in logarithmic form.
Controls in bins	we also include assets and liabilities reported in the bankruptcy filings (see table A5). Source: Bankruptcydata
Panel C: Facility level data	
Log(Total Emission)	Total greenhouse gas (GHG) emissions at the facility in a year. Source: EPA
Log(Total CO2)	Total CO2 emissions at the facility in a year. Source: EPA
Employment	Number of employees at the facility level. Source: NETS
Sales	Number of Sales at the facility level. Source: NETS
Repayment score	ranging from 1 to 100, which indicates the likelihood of a facility repaying its debts. Source: NETS
Repayment risk	defined as the difference between the minimum and maximum score within a month reflects the certainty of the repayment score. Source: NETS
Controls in bins	we also include assets, revenues, liabilities and employment bins reported in the bankruptcy filings. Source: Bankruptcydata

Table B2: Pairwise Correlation of Climate Risk variables

Variables	(1)	(2)	(3)
(1) 1(Brown sector)	1.000		
(2) 1(Large emitter)	0.0313*	1.000	
(3) 1(Bus. Desc. brown)	0.1875*	0.0893*	1.000

Note: The table reports the pairwise correlation of our climate risk variables in the Orbis-BD sample. The brown sector is defined using the IPCC definition of brown, while large emitters are based on the quintile ranking of Scope 1 emissions within each year. Lastly, the business description is based on the SP Capital IQ business description. In the sample, statistical significance is indicated at *p <0.01.

Table B3: Bankruptcy filing by firm classification

	Reorganise							
	Green				**Brown**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Indicator	-0.184	-0.341	-0.220	-0.482*	0.502***	-0.025	0.531***	0.007
	(0.181)	(0.239)	(0.192)	(0.239)	(0.138)	(0.193)	(0.153)	(0.212)
Size and Leverage controls		X		X		X		X
Court District and Year FE			X	X			X	X
Pseudo R^2	0.000	0.324	0.116	0.4225	0.010	0.339	0.115	0.431
N	981	965	981	965	1024	1007	1024	1007

Note: The regression reports the likelihood of companies to file for chapter 11 if they are green (columns 1-4) or brown (columns 5-8) over a control group of neutral firms. The controls are firm size and leverage bins constructed from the bankruptcy dataset. It also includes Court District and Year Fixed Effect. The standard errors are clustered at the court district level. The main difference from 2 is that here we are using the same sample as in table 3 which is smaller, notably the effect for brown firm now lose significance when adding size and leverage controls, however this being a significant smaller sample we should be wary from drawing any significant conclusion.

Table B4: Bankruptcy length for brown firms (control green firms)

Log(process length)				
	(1)	(2)	(3)	(4)
Climate Indicator	−0.104	−0.132	−0.194	−0.142
	(0.160)	(0.170)	(0.162)	(0.169)
R^2	0.003	0.010	0.469	0.507
Adjusted R^2	−0.004	−0.011	0.282	0.316
N	146	141	109	104
Size and Leverage Controls		X		X
Court State and Year Fixed Effect			X	X

Table B5: Results of the OLS Regression for CO2 Emissions

	log(CO2 Emission)					
	(1)	(2)	(3)	(4)	(5)	(6)
Continuation Bias	-7.017*	-7.637**	-2.641	-1.713**	2.351*	-0.580**
	(3.413)	(2.780)	(1.522)	(0.699)	(1.134)	(0.195)
Asset		0.488*	0.0102	-0.0959***	-0.0679	-0.0129
		(0.243)	(0.109)	(0.0179)	(0.0952)	(0.0238)
Revenue		-0.131	-0.252	-0.0738	-0.0132	-0.0461***
		(0.157)	(0.218)	(0.0538)	(0.0684)	(0.00517)
Liabilities		0.165	0.369	0.191*	0.105	0.0282
		(0.212)	(0.214)	(0.0825)	(0.165)	(0.0247)
Employment		-0.208***	-0.0951	-0.0437	-0.0498	-0.0136
		(0.0379)	(0.0707)	(0.0364)	(0.0440)	(0.00823)
$log(CO2Emission)_{t-1}$						0.867***
						(0.0313)
District*Year FE	N	N	Y	Y	N	Y
Sector FE	N	N	N	Y	Y	Y
District*Bankruptcy Year FE	N	N	N	N	Y	N
R^2	0.166	0.416	0.693	0.762	0.791	0.911
Adj. R^2	0.166	0.412	0.676	0.747	0.781	0.905
N	1049	718	695	695	718	684

Note: The regression reports the facility's CO2 emissions from the year of the bankruptcy filing to two years after. For companies that sold the facility the year before the filing, we include that year and the two following years. Continuation bias is based on the probability of continuation after the bankruptcy of firms assigned to a given judge. The controls are bins of revenue, assets, liabilities, and employment constructed from the bankruptcy dataset. We also control for the log of total emissions in the year before filing for bankruptcy. The fixed effects are NAICS sector fixed effects, court district interacted with emission year, and court district interacted with bankruptcy year. The standard errors are clustered at the court district level.

C Orbis data

C.1 Dataset construction

Orbis. We start by downloading all Orbis US data from 1999 to 2023. We discard firms with less than 4 years of data and limited financials. For companies missing state, we retrieve them either by the zip code or by the city name, so we merge zip/city information to state location.[12] We then discard companies with missing states. For the sector, when the NAICS code is missing, we impute it from the SIC code.[13] We keep all non-financial firms (two digits NAICS different than 52).

Orbis-BD merge. The merging process between BD data and Orbis follows these steps:

- In the bankruptcy data, 47% of all companies have an EIN. We can extract EINs from the BVDID number and perform an initial merge. Since only 0.7% of companies have more than one EIN, we will only merge the first two EINs for each company. This approach may result in some bankruptcies not being captured in the data.
- Unmatched Orbis companies are then merged by clean name with BD clean name. Clean names for both samples are constructed by removing punctuation and common business terms.

Subsequently, we obtain a dataset with matched duplicates for the matched by clean name, and we proceed as follows:

- In instances of multiple matches, we retain the matched firms that shares the same State. If duplicates persist, we ensure that the company did not undergo a Chapter 7 bankruptcy before Chapter 11 or multiple Chapter 7 bankruptcies, as this scenario is not feasible. All other duplicates are preserved.
- For any remaining duplicate firms, we calculate a similarity score based on the raw name, and we retain the entry with a score of 1. Any remaining duplicates are discarded.

[12] Location information from https://simplemaps.com/data/us-zips
[13] SIC-NAICS crosswalk from: https://www.naics.com/sic-naics-crosswalk-search-results/

Carbon Emissions. Please note that the classification of large and small emitters is based on the emissions of firms matched with Orbis data. Initially, when utilizing Trucost all sample emissions, a significant portion of matched companies are categorized as large emitters, with only 22 firms falling into the category of small emitters that subsequently went bankrupt (classified within the first to fourth quintiles of emissions). Conversely, there were 172 large emitters among the bankrupted firms.

To address this discrepancy, we adopted an approach where we computed the average emissions across all years and then recalculated the quintiles among the matched firms in Orbis. This adjustment resulted in 43 large emitters and 151 small emitters among the bankrupted firms. Unfortunately, for the remaining firms, emissions data were unavailable.

D S&P-Capital IQ

For robustness, this section replicates our results using S&P Capital IQ rather than Orbis.

D.1 Firms' information

We start our research by gathering data on the entire universe of private and public companies from S&P Capital IQ, covering both active and inactive firms. We discard non-US firms and those in financial sectors, resulting in 1.1 million observations. We complement this data with various financial metrics for these companies, such as total assets, cash reserves, total debt, total liabilities, total revenue, retained earnings, EBIT, EBITDA, and total equity. We also obtain the parent companies' identifier and the firm's establishment date, if the latter is missing, we estimate it based on the earliest year with available data from S&P Capital IQ.

Given the large number of firms with missing data in their financial records, we only include firms with complete data for more than half of the years in our sample. To deal with missing data, we use two methods. One method calculates the average between the most recent observation and the last available one and then fills in the missing values backward. The other method calculates a growth rate from the available data and uses it to estimate the missing variables. While our main analysis focuses on using growth rates for estimation, we also check the sensitivity of our results when using the average method.

To identify the sectors of firms, we use the NACE code, as it's in line with the classification used by major international climate reports like the IPCC. When firms are marked as unclassified or have missing sector information in Capital IQ, we try to guess their sector based on the parent company's sector, if available.[14]

D.2 Merge with Corporate Bankruptcies

We proceed by matching the BD with the universe S&P dataset.[15] This matching task is challenging, primarily because the only common identifiers between the two datasets

[14]Notice that S&P Capital IQ doesn't always provide specific NACE codes, but they use their S&P sector definitions. So, we establish a connection between the NACE and S&P Capital IQ sector codes when both are given. This helps us fill in the NACE code when only the S&P sector information is provided.

[15]See the Appendix for a detailed explanation of this matching process.

are the companies' names and locations.[16] To address this, we implement a multi-stage name-matching approach. First, we match the datasets using exact raw names. Second, for the unmatched subset, we cleanse the companies' names by removing punctuation and common business terms before conducting another matching round. Third, for the unmatched subset, we then employ an exact address matching. Since multiple firms could reside in the same location, we retain only matched firms with a similarity score of names exceeding 85%.[17] Finally, any remaining unmatched firms are matched using a fuzzy name-matching method based on the Dutch Central Bank code available on GitHub.[18]

To ensure accurate matching, we conduct manual verification for a subset of firms. Additionally, we manage duplicates between the bankruptcy data and S&P by verifying if any of the following conditions are met: (i) whether the companies share the same Employer Identification Number (EIN), (ii) whether the duplicate firms belong to the same parent company. If the parent company has filed for bankruptcy, all subsidiaries are considered bankrupt; however, the reverse is not necessarily true. We also take into account (iii) whether the similarity score of company names exceeds 85% and the firms are located in the same state, or (iv) if both companies filed for bankruptcy in the same year according to S&P data. If none of these conditions are satisfied or if there are still multiple matches between BD and S&P data, we discard the observation.

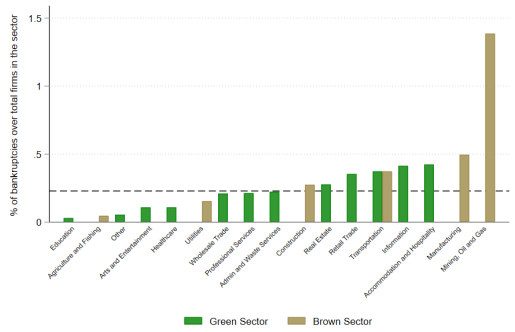
The final merged dataset consists of 107,000 firms, with 2,505 having declared bankruptcy.

D.3 Descriptive Statistics - Capital IQ.

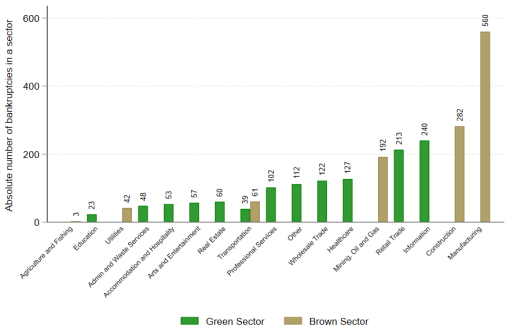
Figure A12 provides a sector-wise breakdown of firm bankruptcies in our sample, with the dotted black line indicating the overall sample average. A preliminary examination of the distribution suggests that companies in emission-intensive sectors, such as Oil and Gas, Mining and Manufacturing exhibit a higher likelihood of bankruptcy compared to the average sample.

[16] In a few cases, we also have the Employer Identification Number (EIN), but its availability in S&P is limited for the entire matching process.
[17] The similarity score is generated using the *matchit* function in Stata.
[18] See the following GitHub page: https://github.com/DeNederlandscheBank/name_matching.

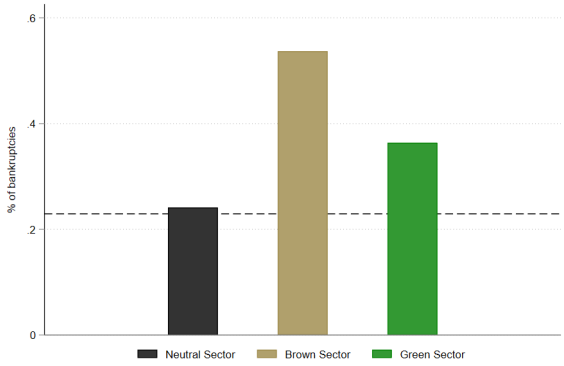
Figure A12: Bankruptcies by sector and business description (SP)



(a) Share of bankruptcies



(b) Total bankruptcies



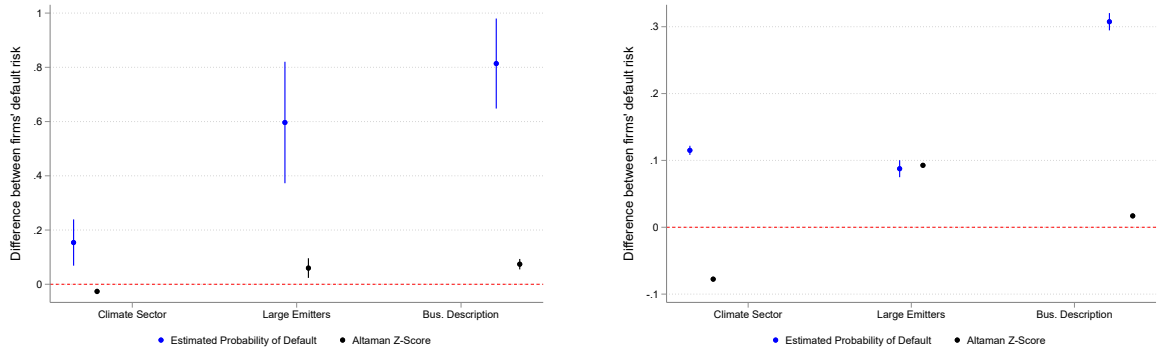
(c) Share bankruptcies by business description

Note: This figure illustrates the proportion of companies (a), the total number of companies (b), and the share of business description (c) that filed for bankruptcies within a specific sector out of the total sample. This ratio is calculated as the number of firms that declared bankruptcy in the matched samples from S&P and DB, divided by the total number of firms in the S&P sample with non-missing company fundamentals. The dashed line indicates the proportion of bankrupted firms in the overall sample.

D.4 Empirical Results for Altman Z score and the estimated probability of default.

Figure A13 illustrates the difference in the average Altman Z score and the estimated probability of default for firms with varying levels of climate risk. Panel (a) shows these estimated results for firms in the year preceding bankruptcy, while panel (b) shows them for non-bankrupted firms. Our analysis reveals that firms with greater climate sensitivity exhibit a higher probability of default. This trend is also observed among non-bankrupted firms and all types of climate sensitivity. Interestingly, firms in climate-sensitive sectors are less likely to be distressed, whereas firms that are large emitters or have a brown business description are more likely to experience financial distress.

Figure A13: Difference in bankruptcies and distressed probabilities (SP).



(a) For firms at bankruptcy year

(b) For firms non-bankrupted

Note: This figure plots the difference in the estimated probability of default (blue) and altman z-score (black) for bankrupted firms in the year prior to default (a) and non-bankrupted firms (b). See that *Data* section for a detailed definition of the climate variables. The estimated probabilities of default are multiplied by 100 for interpretability. *Bus. Description* stands for the Business Description definition of brown and green firm.

E Does Climate Risk Impacts the Type and Cost of Bankruptcy?

In this section, we aim to investigate whether green or brown firms face a heterogenous cost of bankruptcy. Firstly we assess whether companies that are defined as green are more likely to liquidate rather than restructure, then we investigate whether they face different bankruptcy costs, specifically length of the bankruptcy process and percentage of dischargeable over non-dischargeable debt.

E.1 Liquidate or Restructure?

Table B6 compares green and brown firms to a control group of so-called "neutral firms", i.e. firms with a business description that does not include any green or brown terminology The results show a nuanced relationship for green firms with regards to Chapter 7 filings, where coefficients oscillate between mildly negative to slightly positive. Conversely, brown firms exhibit a consistently lower inclination towards liquidation, as evidenced by significantly negative coefficients, this is consistent when including size controls and state and year fixed effects.

Table B6: Filing Type by firm type (control group neutral firms)

	Chapter 7 Filing							
	Green				Brown			
Firm type	-0.057^{*}	0.108^{*}	-0.050^{*}	0.106^{*}	-0.471^{***}	-0.191^{**}	-0.394^{***}	-0.182^{***}
	(0.027)	(0.062)	(0.029)	(0.064)	(0.028)	(0.059)	(0.028)	(0.062)
Constant	0.100^{***}	0.794^{***}	0.790^{***}	-3.723	0.100^{***}	0.807^{***}	0.766^{***}	-3.781
	(0.007)	(0.040)	(0.164)	(35.672)	(0.006)	(0.039)	(0.164)	(32.990)
Observations	39,455	8,329	39,144	8,066	39,455	8,329	39,455	8,329
Size controls		X		X		X		X
State and Year fixed effects			X	X			X	X
Note:				*p<0.1; **p<0.05; ***p<0.01				

E.2 Cost of Bankruptcy

Table B7 regression outcomes suggest a notable trend: brown firms appear to experience shorter bankruptcy processes when compared to their neutral counterparts. This effect is statistically significant in models that include court state and year-fixed effects, indicating a robust association between the environmental classification of brown firms and a reduced duration of bankruptcy procedures. On the contrary, green firms do not show a statistically significant difference in bankruptcy length (table B5 in the Appendix).

Table B7: Bankruptcy length (control neutral firms)

	Dependent variable: log(process length)			
Brown	−0.079	−0.339*	−0.401**	−0.526***
	(0.201)	(0.204)	(0.186)	(0.189)
Observations	1,024	1,007	963	946
R^2	0.0002	0.044	0.215	0.244
Adjusted R^2	−0.001	0.041	0.167	0.196
F Statistic	0.155	15.420	24.789	23.916
Size Controls		X		X
Court State and Year Fixed Effect			X	X
Note:		*p<0.1; **p<0.05; ***p<0.01		

F *Dictionary for green and brown business descriptions (Giannetti et al. (2023)*

Panel A. Brown Industries Keywords

- air transport
- airlines
- airplane
- aluminum
- ammonia
- asbesto
- aviation
- cement
- chemical products
- chemicals
- chlorin
- coal
- copaper
- diesel
- drill
- drilling
- fracking
- fuel oil
- gas
- grabbing
- hydrochlorin
- hydrocarbon
- iron
- kerosene
- logging
- lng
- lpg
- lubricant
- metal fabrication
- methanol
- mines
- mining
- nitric acid
- paraffin
- petrochemical
- petrol
- plastics
- polymer
- refine
- silicium
- soda ash
- steel
- sulfide
- sulphide
- sulphuric

Panel B. Green Industries Keywords (1/3)

- air filter(-ration)
- air quality
- alternative energy
- alternative fuel
- battery(-ies)
- bioclimatic
- biodiesel
- bioenergy
- biofuel
- biogas
- bioliquid
- biolng
- biolpg
- biomethane
- biopower
- bioremediation
- biowaste
- carbon dioxide
- capacitor
- charging point
- charging station
- circular
- circularity
- clean energy
- climate
- cogenerate(-ion)
- contaminate(-ion)
- decommision
- degas
- desalination
- distributed generate
- drinking water
- drone imaging
- ecology
- ecosystem
- electric bus
- electric car
- electric mobility
- electric transport
- electric vehicle
- electromobil
- emission
- endangered
- energy audit
- energy certified(-cation)
- energy conservation
- energy consumption
- energy diagnosis
- energy efficient(-cy)
- energy monitor
- energy optimum(-ization)
- energy performance
- energy recovery
- energy saving

Panel B. Green Industries Keywords (2/3)

- energy storage
- energy transition
- energy yield
- environment protection
- environmental data
- environmental impact
- environmental inspection
- environmental management
- environmental monitor
- environmental policy
- environmental protection
- environmental regulation
- environmental research
- environmental risk
- environmental safety
- environmental solution
- environmental technology
- flywheel
- forest land
- forest management
- forest protection
- forest regeneration
- fuel cell
- fuel consumption
- fuel inspection
- fuel repair
- gas capture
- green
- heat pump
- heat recovery
- hybrid car
- hybrid vehicle
- hybrid vessel
- hydraulic
- hydrogen
- insulate(-ion)
- led
- lighting control
- low carbon
- low power
- marine energy
- material recovery
- methane leakage
- natural forest
- nitrogen
- nox
- nuclear
- ocean energy
- oil cleanup
- oil removal
- oil spill
- organic
- photovoltaic
- pollutant

Panel B. Green Industries Keywords (3/3)

- pollution
- potabilization
- proofing
- protected area
- rail transport
- railway
- rainwater
- rainforest
- reforestration
- regenerative farm
- renewable
- retrofit
- sealing
- seeding
- smart energy
- solar
- static var
- superconduct
- sustainability
- sustainable
- thermal
- thermodynamic
- thermoelectric
- thermostat
- trigenerate(ion)
- ultrasonic humidifier
- uranium
- voltage regulation
- waste consulting
- waste recovery
- waste removal
- waste reuse
- waste solution
- wastewater system
- water collection
- water consulting
- water filter(-ration)
- water purification
- water quality
- water remediation
- water reuse
- water safety
- water scarcity
- water treatment
- wildlife