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Climate Transition Risk and Debt Capital Costs: Empirical Evidence from the Energy and Utilities Sectors

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Abstract: Although transition risks from climate change, such as regulatory shifts, market disruption, consumer preferences, and evolving technologies, are increasingly acknowledged by financial institutions, most empirical research has focused on equity markets, leaving the impact on corporate debt markets underexplored. In particular, few studies have examined how different dimensions of transition risk affect the cost of debt (COD), especially across firms operating in high-emission sectors. This paper addresses this gap by investigating whether and how climate-related transition risks are priced into the COD for international utilities and energy companies. Using a balanced panel dataset of 219 firms from 2012 to 2017, we propose a two-step approach. First, we apply principal component analysis to construct a multidimensional transition risk index. We identify two distinct components: a contemporaneous risk factor (called present risk) capturing firms' existing energy portfolio composition and emission intensity, and a forward risk factor (called future risk) capturing future-oriented exposures such as fossil fuel reserves and investment patterns. Second, we use panel regression analysis, which shows that the current risk dimension significantly increases borrowing costs throughout the period whereas the future risk dimension exhibits statistical significance exclusively from 2015 onward, coinciding with rising investor awareness following the Paris Agreement. These findings contribute to the growing literature on climate finance by offering a nuanced understanding of how transition risks are internalized in corporate debt pricing.

Keywords: climate risk, cost of debt, carbon emissions, transition risk

1. Introduction

The Paris Agreement marked a turning point in global climate policy by uniting nat+ions in a shared objective: to limit the global temperature increase to well below 2°C above pre-industrial levels, with efforts to cap it at 1.5°C. Achieving this goal requires reaching carbon neutrality by 2050, which entails a complete reduction in net greenhouse gas (GHG) emissions [1]. This transition demands profound and rapid changes in socio-economic systems—particularly in carbon-intensive sectors such as energy and utilities, as shown in Figure 1 [2].

Considerable attention has been paid recently to climate-induced risks in the financial sector, with particular emphasis on transition risks linked to decarbonization efforts. These transition risks include potential losses arising from regulatory shifts, technological disruption, and changes in market or consumer behavior. Central banks and financial regulators have begun assessing the exposure of financial institutions to these risks [3, 4]. Notably, Mark Carney's 2015 speech brought widespread attention to the systemic implications of climate-related financial risk, especially in the case of a sudden and disorderly transition [5].

Despite growing awareness, the degree to which transition risks are integrated into financial decision-making, particularly in debt markets, remains unclear. Although equity markets have received greater research attention, the pricing of transition risks in corporate debt is less well understood. However, this is a crucial issue: if creditors do not adequately assess firms' exposure to transition risks, they may misprice loans and bonds, potentially compromising financial stability.

This paper contributes to literature by analyzing how transition risk affects the cost of debt (COD). We focus on firms in the energy and utilities sectors, which are widely regarded as particularly vulnerable to decarbonization policies. Using data from 2012 to 2017, we construct a composite index of transition risk based on multiple firm-level indicators and analyze its impact on borrowing costs.

This paper is organized as follows. Section 2 surveys existing literature and formulates the hypotheses. Section 3 develops the data and empirical strategy. Section 4 discusses and interprets the results, and Section 5 concludes.

2. Literature Review and Testable Hypotheses

This paper contributes to two fields of literature. The first field examines how climate transition risks affect the cost of capital debt, with mixed empirical findings. The second field is a well-established body of research analyzing the links between corporate financial and extra financial performances, particularly corporate social performance and financial returns.

The impact of transition risk on the stock market is gaining recent attention in literature. For instance, Gorgen et al. [6] and In et al. [7] reported that integrating carbon risk into investment strategies can

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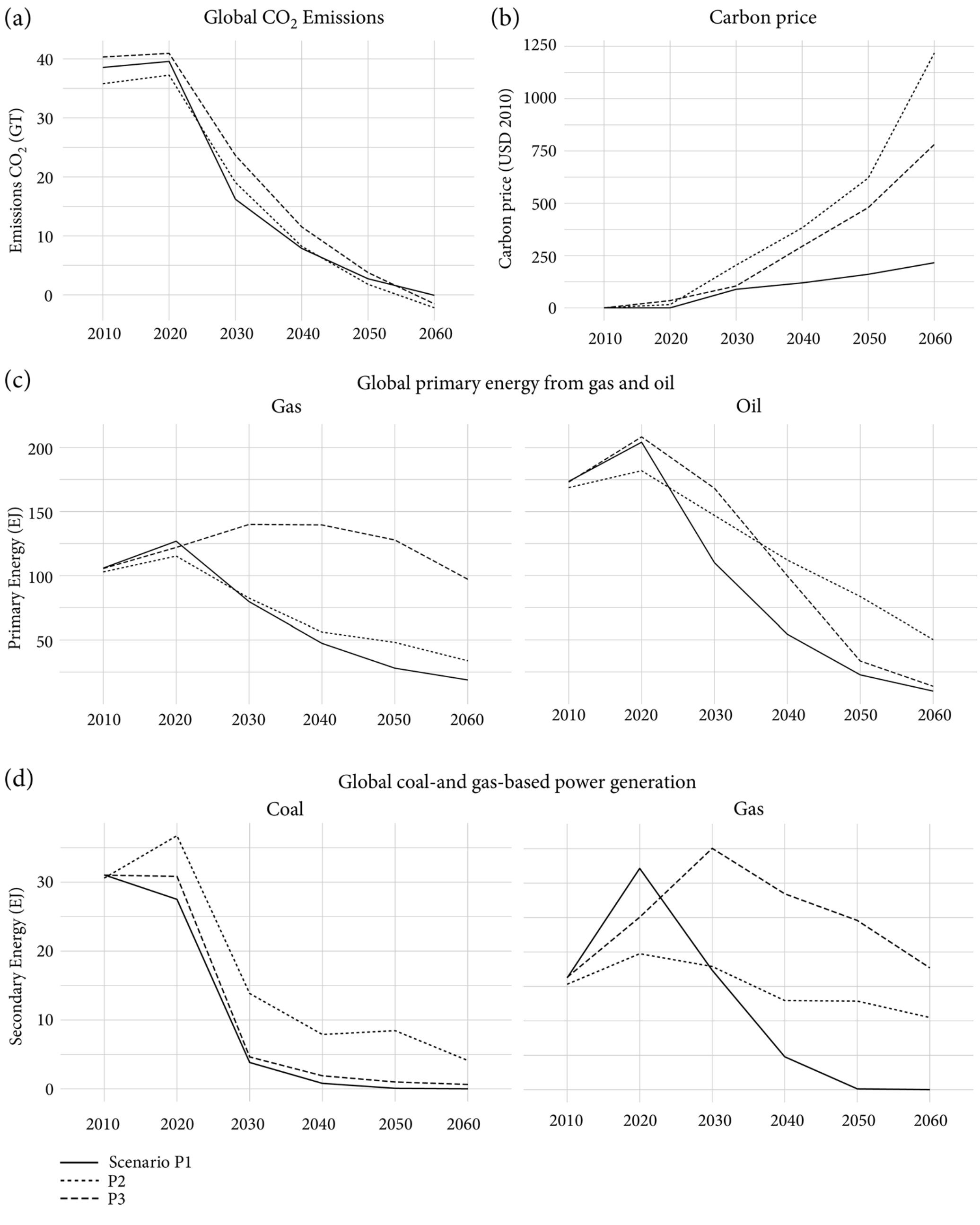
Figure 1
Evolution of energy-related variables from three illustrative scenarios that limit global warming to 1.5°C



yield comparable or even superior risk-adjusted returns, suggesting that carbon pricing is not fully reflected in current valuations. In contrast, Ilhan et al. [8] argued that transition risk is already partially embedded in market prices. However, most of this literature focuses on the equity market. The debt market—despite its distinctive risk-return characteristics—has received comparatively less attention. Notably, Trinh et al. [9] showed that companies with higher climate exposure face higher CODs in the European market, highlighting the relevance of transition risk for creditors as well.

Complementing this, Shahrour et al. [10] provided sector-specific evidence that transition risks are priced into credit markets, underscoring the importance of accounting for climate exposure in credit assessments. Similarly, Shahrour et al. [11] offered a theoretical framework linking firm-level characteristics to climate risk exposure, and Economidou et al. [12] demonstrated that sustainability ratings—often used as proxies for transition risk—have material implications for financial markets.

Alongside this, the literature on corporate social and environmental performance has long debated its financial implications. Although early studies questioned whether such practices compromised returns, meta-analyses like that of Friede et al. [13] and more recent work by Zerbib [14] generally find a positive—if modest—association. However, this research has primarily emphasized the equity market, leaving the effects on debt underexplored. Breitenstein et al. [15], for example, emphasized the risk-reducing potential of integrating environmental responsibility into financial strategies and noted the need for more nuanced understanding of climate-related financial risks.

Theoretically, transition risks may influence a firm's COD through several channels: regulatory shifts (e.g., carbon taxes), market changes (e.g., demand for green technologies), technological innovation (e.g., renewable energy solutions), and social pressures (e.g., changing consumer preferences). These factors can affect revenues, operating costs, capital expenditures, and asset values—including the devaluation of stranded assets and production equipment—ultimately affecting a firm's creditworthiness [16].

From a creditor's perspective, lending decisions involve assessing credit risk—defined as the likelihood of default—based on economic, solvency, and liquidity factors. This influences not only loan conditions (e.g., amount and collateral) but also borrowing costs [17]. As firms face the multifaceted challenges of the low-carbon transition, their exposure to these risks can raise creditors' perceived risk and their COD.

However, there is evidence that financial institutions may still misprice these risks. Chenet et al. [18] argued that flaws in risk models—particularly their assumptions of rational behavior and temporal consistency—undermine their ability to capture long-term climate risk. Moreover, conventional financial models often rely on limited historical data and assume normal return distributions, making them ill-suited to address the deep uncertainty and fat-tailed risks associated with climate transition.

Although transition risk is increasingly acknowledged in equity markets, debt instruments differ in important ways. Bonds and loans have fixed maturities and downside-focused risk assessments, with a greater emphasis on default likelihood. As such, transition risks may be priced differently in debt markets. However, empirical studies remain limited. Trinh et al. [9] documented a positive link between carbon intensity and COD for European firms, suggesting that lenders are beginning to integrate climate concerns. This aligns with earlier findings on the relationship between environmental performance and credit spreads [19, 20]. Our study extends this literature by examining whether transition risk affects CODs for firms in the energy and utilities sectors—two industries particularly vulnerable to decarbonization policies [3, 4].

Although carbon intensity remains the most widely used proxy for transition risk [7, 8, 21], it captures only part of the picture. Factors such as corporate governance, technological investment, and energy mix are also important. Gorgen et al. [22] offered a more comprehensive approach by constructing a composite climate risk score based on 55 variables across dimensions such as value chain, public perception, and adaptability. Our methodology builds on this multidimensional approach by employing principal component analysis (PCA) to synthesize transition risk indicators.

In summary, the contribution of this paper to the literature is twofold. First, it decomposes transition risk across two high-exposure sectors: energy and utilities. Second, it explores the effect of transition risk on the COD for international firms—extending a research stream that has largely focused on equity markets and single-country studies. If lenders are indeed integrating transition risk into credit evaluations, then firms with greater exposure should exhibit higher borrowing costs.

To advance this line of research, we formulate two testable hypotheses.

H1: Higher transition risk is associated with a higher COD.

According to asset pricing and corporate finance theory, the COD reflects the risk premium required by creditors to compensate for credit risk. In the context of climate change, transition risk—arising from decarbonization policies, shifting consumer preferences, technological changes, and litigation—increases firm-specific uncertainty and the likelihood of cash flow disruptions or stranded assets. As a result, debt investors adjust credit assessments and pricing to reflect this elevated risk, potentially increasing borrowing costs for more exposed firms. Empirical studies confirm that creditors may tighten lending terms or reduce exposure to high-risk firms, particularly as institutional investors and lenders increasingly integrate ESG and climate-related risks into their financial models [8, 23]. Therefore, Hypothesis 1 is grounded in the theory of risk-adjusted pricing and credit risk assessment.

H2: The impact of transition risk on the COD becomes more pronounced in the post-2015 period.

This hypothesis builds on theories of policy credibility and market learning. The 2015 Paris Agreement marked a pivotal moment in global climate governance, establishing binding commitments to limit global warming and signaling stricter future climate policies. According to theories of policy uncertainty and investor responsiveness [24], financial markets adjust gradually to new, complex information—especially for long-term risks such as climate change. The Paris Agreement enhanced the credibility of decarbonization pathways, increasing the salience of transition risk in investor assessments.

This shift is driven by several mechanisms—notably, revised expectations regarding the cost of carbon-intensive activities, leading to greater pricing of transition risk post-2015 [25], and regulatory and institutional changes such as the Task Force on Climate-Related Financial Disclosures and EU sustainable finance initiatives, which embedded climate risk into financial practices. Moreover, empirical evidence documents that investor reactions to climate risk disclosures intensified after major climate policy events [26, 27].

Thus, the Paris Agreement represents a structural break after which transition risk became more influential in determining the cost of corporate debt.

3. The Climate Transition Risk Index and Impact

3.1. Data and variables

Our analysis is based on a balanced panel dataset of 1,314 observations for 117 energy and 102 utilities companies over the 2012–2017 period using three sources of information (Figure A1): the Trucost GHG emissions and reserves database, the Orbis (Bureau Van Dijk) financial data, and the Vigeo Eiris equitics and transition risk data [28]. The variables are defined and fully described in Table A1.

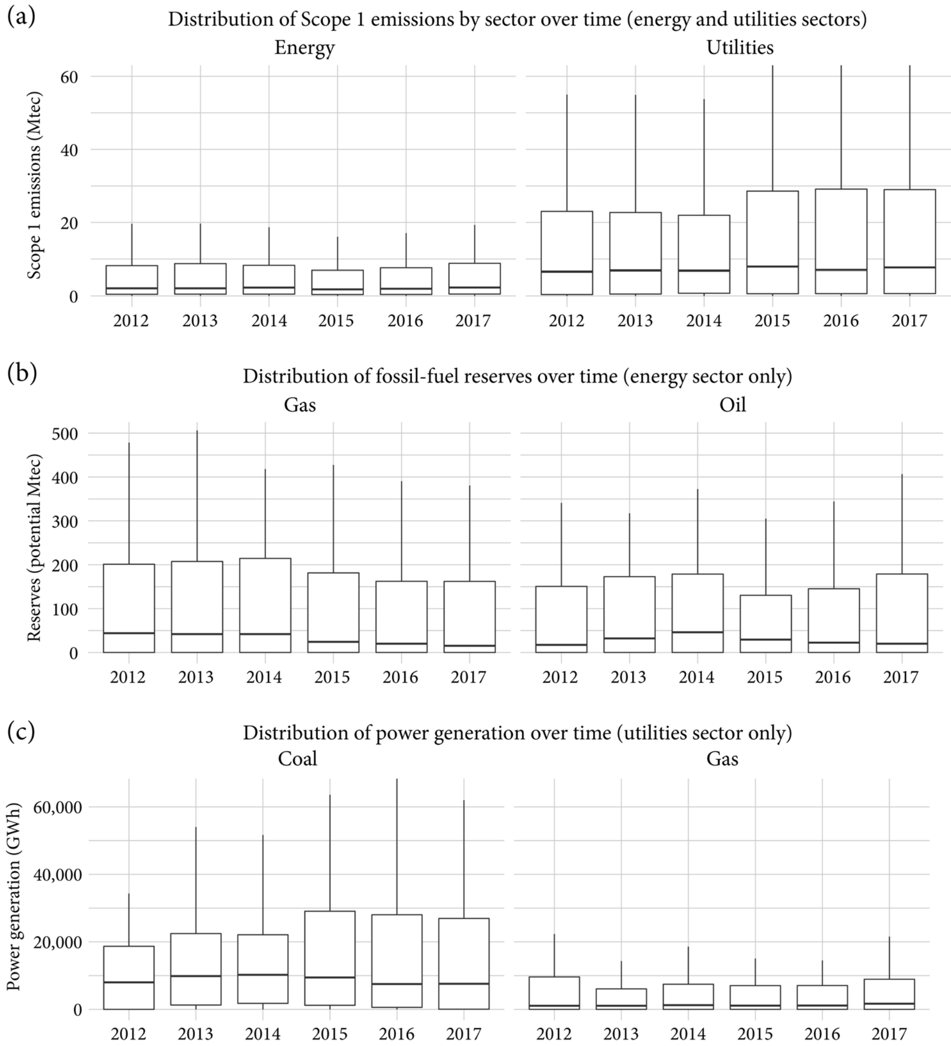
The primary goal of our analysis is to isolate the core components underlying transition risk in the energy (oil, gas, and combustible fuels) and utilities (electric, gas, water, multiutilities, and independent power and renewable electricity producers) industries.[1] To achieve this, we first select all relevant indicators for the energy and utilities sectors that exhibit sufficient data coverage (exceeding 80%) in the Trucost database. More precisely, three types of indicators are retained: GHG emissions, fossil fuel reserves, and power generation.

Regarding GHG emissions, the GHG protocol distinguishes between Scope 1 emissions (originating from direct fossil fuel combustion and production processes), Scope 2 emissions (resulting from purchased energy consumption), and Scope 3 emissions (all other indirect emissions, including supply chain activities, transportation, outsourced operations, and waste management). For energy and utilities firms between 2012 and 2017, emissions are overwhelmingly driven by Scope 1 (direct combustion), and Scope 3 (product end-use) and Scope 2 emissions are negligible notably because fuel combustion at generation facilities produces the majority of the sector emissions and electricity used in operations is minor [23]. For example, CDP [29] documented that Scope 1 accounts for 85%–95% of emissions in electric utilities and oil & gas and Scope 2 is often <5%. We thus consider only Scope 1 and Scope 3 emissions.

Figure 2(a) illustrates the right-skewed distribution of Scope 1 emissions across firms in the energy and utility sectors. Although the distribution remains skewed throughout the sample period, we observe that the median Scope 1 emissions remain relatively stable in the energy

[1] https://classification.codes/classifications/industry/gics/

Figure 2
Time evolution of transition risk variables in the energy and utilities sectors



sector and exhibit a slight upward trend in the utility sector. This reflects the persistence—and in some cases expansion—of direct emissions from fossil-based operations during the 2012–2017 period. To account for differences in firm size and to improve comparability across firms and time, we normalize Scope 1 emissions by total assets and apply the natural logarithm in our empirical analysis.

Regarding fossil fuel reserves, we analyze proven and probable[2] natural gas and oil reserves, excluding coal due to missing data, with Trucost expressing them as GHG emissions embedded in reserves. Figure 2(b) shows a right-skewed distribution, a zero median due to utility companies, and a decreasing trend over time. We also include capital expenditures on oil and gas exploration. For PCA, reserves and capital expenditures are normalized by total assets and log-transformed.

For power generation, we analyze annual coal- and gas-based output in GWh, normalized by total assets and log-transformed for PCA. Figure 2(c) shows the distribution of total electricity generation across firms. Although median output stays fairly stable, some firms increase generation, widening the distribution. This helps in explaining trends in Scope 1 emissions and operational scale during the period. Table 1 presents the correlation matrix of all transition risk variables.

3.2. Methodology

To address the two hypotheses of the study, namely, that H1 increased climate-related transition risk is associated with a higher COD and H2 that this relationship strengthens following the 2015 Paris Agreement, we adopt a two-step approach. In the first step, we construct two distinct indices of transition risk—"current risk" and "future risk"—using PCA. This method offers several advantages: it derives endogenous weights objectively from the underlying data structure, captures the correlations among multiple transition-related variables, and reduces dimensionality while retaining explanatory power. The PCA is conducted separately for the energy and utilities sectors to account for structural heterogeneity, yielding sector-specific risk scores that are robust and interpretable.

In the second step, we estimate fixed-effects panel regression models that examine the relationship between transition risk and the COD. Two models are estimated. Model 1 includes firm- and year-fixed effects alongside financial control variables to mitigate omitted variable bias and unobserved heterogeneity. Model 2 introduces interaction

[2] Proven fossil fuel reserves have greater than 90% certainty of being recovered while still economically viable to do so, whereas probable reserves have a level of certainty between 50% and 90%. https://www.spe.org/en/industry/petroleum-reserves-definitions/, visited on April 3, 2020.

Table 1
Pearson correlation matrix heatmaps of PCA transition risk variables for each sector

Energy	Scope 1	Scope 3	GWh gas	GWh coal	Res. gas	Res. oil	Capex oil & gas
Scope 1							
Scope 3	***						
GWh gas	***	***					
GWh coal	***	***	***				
Res. gas	***	***	***	***			
Res. oil	***	***	***	***	***		
Capex oil & gas	***	***	***	***	***	***	

Utilities	Scope 1	Scope 3	GWh gas	GWh coal	Res. gas	Res. oil	Capex oil & gas
Scope 1							
Scope 3	***						
GWh gas	***	***					
GWh coal	***	***	***				
Res. gas	***	***	***	***			
Res. oil	***	***	***	***	***		
Capex oil & gas	***	***	***	***	***	***	

Note: Colors represent the strength and direction of the correlations. Dark red = strong negative correlation (−1), white = no correlation (0), and dark blue = strong positive correlation (+1). Asterisks inside cells denote statistical significance at the 10% level (*), 5% level (**), and 1% level (***). Diagonal cells shaded in dark blue represent self-correlation (value = 1).

terms between transition risk scores and a post-2015 dummy variable to capture the differential effect of transition risk after the Paris Agreement. This specification approximates a difference-in-differences framework, enabling us to assess changes in investor sensitivity to transition risk over time. By controlling for firm fundamentals and applying such econometric techniques, this strategy reduces concerns regarding endogeneity, including reverse causality and measurement error.

3.2.1. The transition risk index

To construct the transition risk index from the transition risk variables, we follow the method of Nicoletti et al. [30] and Capelle-Blancard et al. [31], which is based on PCA. One advantage of the PCA method is that it enables the creation of a composite score from multiple variables without relying on expert-assigned weights. Compared to other methods such as equal weighting or the mixed approach used by Gorgen et al. [22][3], it also allows us to take into account correlations between variables and a larger proportion of the variance in the dataset is explained.

We first present the exploratory analysis results, followed by the steps for constructing transition risk scores.

By recognizing that valuations are generally conducted on a sectoral basis, we apply PCA separately to the energy and utilities sectors. Table 1 summarizes the correlation structure of the transition risk variables in each sector. The high level of correlation suggests that the PCA method is appropriate, and the Kaiser–Meyer–Olkin (KMO) statistics of 0.72[4] for the energy sector and 0.67 for the utilities sector confirm this. Table 2 displays the sector-specific factor loadings from the PCA. We retain two components selected using the Kaiser criterion.[5] Both sectors share the same components but with reversed importance. PC1 (Scope 1, Scope 3, and power generation) represents current risk, whereas PC2 (reserves and investments) reflects future risk. Variance in the energy sector is mainly driven by future risk, whereas in the utilities sector, it is dominated by present risk.

Following Capelle-Blancard et al. [31], we construct current and future risk scores by selecting key variables per component and setting others to zero. Each variable is assigned a weight according to its contribution to explained variance, calculated as the normalized squared loading, with the procedure applied separately for each sector. The resulting weights are reported in Table 2.

In Table 2, regarding exploratory PCA, PC1 and PC2 capture the majority of the variance in the energy (.e) and utilities (.u) sector data using the same underlying variables. Despite differing in order of importance across sectors, one component consistently reflects future transition risk (PC1.e, PC2.u), and the other captures current transition risk (PC2.e, PC1.u). Regarding score construction, each transition risk score is constructed using only the variables with the highest loadings on the relevant component, as identified in Table 2; all other variables are excluded. Weights are based on squared factor loadings, which indicate the proportion of each variable's variance explained by the component. For example, the first component that represents the future transition risk (Fut.risk) of the energy sector (.e) is computed as follows: Fut.risk.e = 0.34 ∗ Reserves gas + 0.34 ∗ Reserve soil + 0.32 ∗ Capex oil & gas.

3.2.2. Panel regression models

1) Dependent and control variables

The dependent variable is the COD. To measure corporate borrowing costs, we calculate the firm's interest expense in year t relative to its interest-bearing debt for the same period. To reduce noise from year-end debt fluctuations, we trim data at the 5th and 95th percentiles. Figure 3 illustrates the COD trends over time and by sector, showing an increase for the energy sector after 2015, while remaining stable for utilities.

To account for firms' economic and financial characteristics, our regression model includes control variables based on prior studies [19, 20], with all values reported at fiscal year-end:

[3] They develop a climate risk score (CRS) using 55 transition risk variables across three dimensions: value chain, public perception, and adaptability. Each variable is binarized based on its median, averaged within its dimension, and the three dimension scores are weighted by expert judgment.
[4] Factor analysis (e.g., PCA) is appropriate for a dataset if the KMO statistic is above 0.6.
[5] Components with an eigenvalue above 1.00 are retained.

Table 2
Exploratory PCA results and transition risk score development

Energy utilities variable	PC1.e	PC2.e	PC1.u	PC2.u
Scope 1	0.32	**0.50**	**-0.54**	0.18
Scope 3	0.26	**0.48**	**-0.45**	0.21
GWh gas	0.25	**0.33**	**-0.38**	0.09
GWh coal	0.31	**0.31**	**-0.52**	0.06
Reserves gas	**-0.47**	0.37	0.15	**0.61**
Reserves oil	**-0.47**	0.34	0.08	**0.54**
Capex oil & gas	**-0.48**	0.26	0.24	**0.50**
Eigenvalue	3.18	1.52	2.81	1.84
Variance explained by component (%)	45.36	21.77	40.19	26.25
Cumulative variance	45.36	67.13	40.19	66.45
Score construction	**Energy**		**Utilities**	
	FutureRisk.e	**CurrentRisk.e**	**CurrentRisk.u**	**FutureRisk.u**
Scope 1	0.00	**0.32**	**0.33**	0.00
Scope 3	0.00	**0.25**	**0.24**	0.00
GWh gas	0.00	**0.19**	**0.15**	0.00
GWh coal	0.00	**0.24**	**0.28**	0.00
Reserves gas	**0.34**	0.00	0.00	**0.39**
Reserves oil	**0.34**	0.00	0.00	**0.29**
Capex oil & gas	**0.32**	0.00	0.00	**0.32**

Figure 3
Temporal distribution of the COD

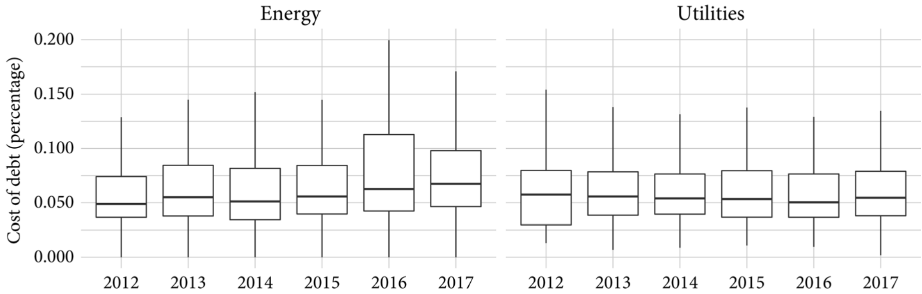


Table 3
Average distribution of variables in the fixed-effects model

	Variable	Mean	St. Dev.	Min	Max
1	COD	0.06	0.04	0.01	0.19
2	CurrentRisk	0.59	0.15	0.21	0.87
3	FutureRisk	0.08	0.14	0.00	0.50
4	Size	16.20	1.27	10.92	19.83
5	Leverage	0.31	0.18	0.01	2.57
6	InterestCoverage	4.81	5.52	-6.01	26.80
7	LiquidityRatio	1.15	1.53	0.03	32.35
8	ROA	5.21	22.60	-282.68	51.98
8	MarketBook	0.61	0.55	0.02	8.71

- Size: natural logarithm of assets in year t. Larger firms are seen as less risky, reducing CODs.
- Leverage: long-term debt/total assets. Higher leverage signals greater default risk, increasing CODs.
- Return on Assets: net income/total assets. Greater profitability lowers CODs.
- Interest Coverage: EBIT/interest expenses. Higher coverage reduces liquidity risk, lowering CODs.
- Liquidity Ratio: current assets/current liabilities. Greater liquidity reduces risk and CODs.
- Market-to-Book Ratio: market capitalization/book value of assets. Higher valuation suggests investor confidence, decreasing CODs.

Tables 3 and 4 present the descriptive statistics and correlation of variables in the fixed-effects model.

Table 4
Pearson correlation matrix heatmap of the fixed-effects model variables

	COD	CurrentRisk	FutureRisk	Size	Leverage	Int.Coverage	Liq.Ratio	ROA	MarketBook
COD									
CurrentRisk									
FutureRisk		***							
Size	***	***	***						
Leverage	***		*	**					
Int.Coverage	***	*	**		***				
Liq.Ratio		***		***	*				
ROA	***			***	***	***	*		
MarketBook	**	***	**	***	***	***	***		

Note: Colors represent the strength and direction of the correlations. Dark red = strong negative correlation (−1), white = no correlation (0), and dark blue = strong positive correlation (+1). Shades in-between indicate intermediate correlation strengths. Asterisks inside cells denote statistical significance at the 10% level (*), 5% level (**), and 1% level (***). Diagonal cells shaded in dark blue represent self-correlation (value = 1).

2) Baseline fixed-effects model

Our analysis begins with a panel linear regression model that estimates the relationship between firms' COD and their exposure to climate transition risks. The baseline model is specified as Equation (1) follows:

$$\begin{aligned} COD_{it} &= \beta_0 + \beta_1(CurrentRisk)_{it} + \beta_2(FutureRisk)_{it} \\ &+\beta_3(Size)_{it} + \beta_4(Leverage)_{it} + \beta_5(InterestCoverage)_{it} \\ &+\beta_6(LiquidityRatio)_{it} + \beta_7(ROA)_{it} \\ &+\beta_9(Sector)_i + a_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where, for a company i at year t, α denotes firm fixed effects, λ denotes year fixed effects, ε is the idiosyncratic error term, and the independent variables are those defined immediately above. This model provides a foundational understanding of how contemporaneous and forward-looking climate risks are priced in by debt markets. In this specification, firm fixed effects control for time-invariant, unobserved heterogeneity across firms, and year fixed effects absorb common macroeconomic shocks and regulatory trends over time.

3) Extended model: post-Paris agreement interaction terms

To explore the possibility that market pricing of future climate transition risk changed in the aftermath of the Paris Agreement 2015—a landmark policy event—we extend the model with interaction terms:

$$\begin{aligned} COD_{it} &= \beta_0 + \beta_1(CurrentRisk)_{it} + \beta_2(FutureRisk)_{it} \\ &+\beta_3(Size)_{it} + \beta_4(Leverage)_{it} + \beta_5(InterestCoverage)_{it} \\ &+\beta_6(LiquidityRatio)_{it} + \beta_7(ROA)_{it} + \beta_8(MarketBook)_{it} \\ &+\beta_9(Sector)_i + \beta_{10}(CurrentRisk{*}ParisAgreement)_{it} \\ &+\beta_{11}(FutureRisk{*}ParisAgreement)_i + a_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where ParisAgreement is a dummy variable equal to 1 for years after 2015 and 0 otherwise. The interaction terms assess whether the pricing of climate transition risk changed following the Paris Agreement.

3.2.3. Results

Table 5 presents the panel regression results. In the baseline model (column 1), we find a significant positive coefficient for current transition risk, suggesting that markets associate higher immediate climate risk with higher borrowing costs, confirming hypothesis H1. In contrast, future transition risk does not exhibit a statistically significant relationship, potentially indicating that markets are less responsive to anticipated climate exposures without a triggering event or regulatory impetus. In the extended model (column 2), the interaction term for future transition risk becomes statistically significant, and the main effect remains insignificant. This suggests that investors began to price future climate risks only after the Paris Agreement, implying a

Table 5
Linear panel regression models

	COD	
	Model (1)	**Model (2)**
CurrentRisk	0.058**	0.057**
	(0.025)	(0.025)
FutureRisk	0.001	-0.005
	(0.028)	(0.027)
Size	-0.033***	-0.030***
	(0.010)	(0.009)
Leverage	-0.082*	-0.082*
	(0.044)	(0.044)
InterestCoverage	-0.001***	-0.001***
	(0.0003)	(0.0003)
LiquidityRatio	-0.00003	-0.0002
	(0.0004)	(0.0004)
ROA	-0.0002***	-0.0002***
	(0.0001)	(0.0001)
MarketBook	0.007**	0.007*
	(0.003)	(0.004)
CurrentRisk * ParisAgreement		-0.007
		(0.014)
FutureRisk * ParisAgreement		0.038**
		(0.018)
Number of observations	870	870
R^2	0.256	0.270
Adjusted R^2	0.039	0.055
F statistics	21.036*** (df = 11; 673)	19.147 (df = 13; 671)

Note: Asterisks denote statistical significance at the 10% level (*), 5% level (**), and 1% level (***).

structural shift in expectations and valuation practices triggered by a global policy commitment to decarbonization. The interaction term for current risk remains insignificant, likely because current risks are already internalized regardless of the policy change, partially validating H2. As a robustness test, we use Vigeo Eiris's transition risk score (335 observations). Its positive but insignificant effect suggests that the relationship between transition risk and COD depends on how risk is measured.

Robustness checks using alternative measures may yield weaker results—not necessarily because the original findings are invalid, but potentially due to limitations in the alternative metric. For instance, measures based on expert judgment may lack transparency and methodological clarity. This outcome does not detract from the robustness of our primary findings; rather, it underscores the advantages of our PCA-based measure, which adheres to established standards in quantitative financial research. Constructed via PCA, our approach is data-driven and replicable and assigns endogenous weights to correlated variables, in line with best practices for identifying latent constructs [32]. PCA offers statistical efficiency and transparency by avoiding subjective weighting schemes, thereby enhancing the reliability and credibility of empirical research. By comparison, although widely used in practice, the Vigeo rating system is built on proprietary and non-public methodologies, which have been found to exhibit lower inter-rater reliability and methodological divergence [33, 34].

4. Discussion and Policy Implications

This empirical analysis focuses on two critical sectors that are not only essential to the energy transition but also particularly vulnerable to transition risk [3, 4]. From a financial market perspective, the energy sector has been the subject of numerous studies examining the impact of oil prices [35], their volatility [36], levels [37], and supply and demand shocks [38] on stock prices and stock markets in general [39] and on sovereign bonds [40]. Although oil prices constitute a component of transition risk (market risk), less attention has been given to transition risk in its entirety, including carbon risk [22]. Most studies addressing transition risk focus on the carbon intensity of companies [7, 8, 21]. However, this metric overlooks sector-specific transition risk factors and focuses solely on current emissions. For the energy and utilities sectors, our analysis of seven variables related to emissions, their sources (type of fossil energy), reserves, and investments reveals two key components: current risk and future risk. This finding underscores the necessity of developing sector-specific and forward-looking approaches to assess transition risk.

Next, we investigate whether these two components are reflected in the COD for these companies. Griffin et al. [41] documented the stock market's reaction to a 2009 academic paper that highlighted the stranded asset risk associated with an energy transition aimed at limiting global warming. This publication led to an average stock price decrease of 1.5%–2% for the largest US oil and gas firms. Although this reaction indicates investor recognition of this emerging risk, the authors noted that it remains limited. A survey by Krueger et al. [23] shows that an increasing number of investors believe that climate risks could have financial implications for their portfolios. Our empirical specification includes an interaction term between future transition risk and a post-2015 dummy variable, which captures the differential effect of forward-looking risk after the Paris Agreement. This interaction term is statistically significant, whereas the standalone effect of future transition risk is not. This pattern is not coincidental but meaningful. This approach approximates a difference-in-differences (DiD) framework, which is widely used in empirical economics to identify structural breaks around policy changes by estimating how the sensitivity to future risk changes in firms over time, around a clearly identified global policy event. Thus, although our model is a linear regression in form, the time-interacted term functions as a quasi-experimental identification strategy, allowing us to infer that investor attention to future transition risk increased after 2015. Our finding is also consistent with existing literature on climate finance, which identifies 2015 as a pivotal turning point [23, 25].

From a policy perspective, this distinction between current and future risks emphasizes the need for greater incentives for investors to adopt long-term, forward-looking approaches. This analysis reaffirms the need for financial regulators to urge investors to systematically incorporate climate risks into their decision-making processes. To achieve this, investors must have access to reliable and consistent climate-related data [42]. It is therefore crucial that non-financial disclosures by companies are standardized and harmonized at the international level, beyond the current voluntary initiatives. Although certain indicators should be cross-sectoral, our results highlight the importance of sector-specific communication, particularly for energy and utilities companies, where metrics such as fossil fuel production, reserves, and energy mix are often reported inconsistently across firms. Additionally, the fact that only current risk was considered before 2015 underscores the "tragedy of the horizon" [5]. Beyond the development of climate stress tests and the availability of data, regulators play a crucial role in extending the traditional financial risk management horizon [42].

Conversely, this gradual incorporation of transition risk by investors may impose a double burden on energy and utilities companies. As the COD increases for the most exposed firms, their ability to finance the investments necessary to transform their assets or change their business models may be hindered. To mitigate this double penalty, it is essential that the consideration of climate risks is accompanied by enhanced dialogue between investors and counterparties [43].

This analysis adds to the growing literature on financial risks associated with climate change, which encompasses both physical and transition risks, explored through historical and forward-looking methods across various sectors.

5. Conclusion

Since the 2015 Paris Agreement, transition-related financial risks have gained prominence. This study examines how key components of transition risk affect the COD in two high-emission sectors: energy and utilities. Our findings identify two main drivers of transition risk in these sectors: current risk, linked to direct and indirect emissions and energy mix, and future risk, associated with investments and fossil-fuel reserves that could lead to future emissions. The latter is closely related to stranded assets, which risk devaluation as they become misaligned with the Paris Agreement's climate goals. Furthermore, our analysis shows that present risk consistently affects the COD across all periods and future risk only becomes significant after 2015, suggesting a delayed acknowledgment of long-term transition risk by debt holders. However, our results depend on the chosen method for measuring transition risk. Using an alternative indicator, we find no significant correlation with the COD.

This study has two main limitations. First, data availability and coverage are restricted, particularly before 2015, leading to their exclusion from the PCA. Second, other dimensions of transition risk, such as reputational and governance risks, are not considered. In the energy sector, governance is crucial in shaping oil and gas production decisions [44] and affects the management of emissions and fossil resources. Future research could incorporate climate risk management data from initiatives such as the Carbon Disclosure Project to address these gaps.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are a property of Trucost ESG Analysis S&P Global, Orbis Moody's, and Vigeo Eiris VE Moody's, subject to data user license agreements, and are not openly available.

Author Contribution Statement

Vincent Bouchet: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Patricia Crifo:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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Appendix

Figure A1
Number of companies by GICS sector and industry

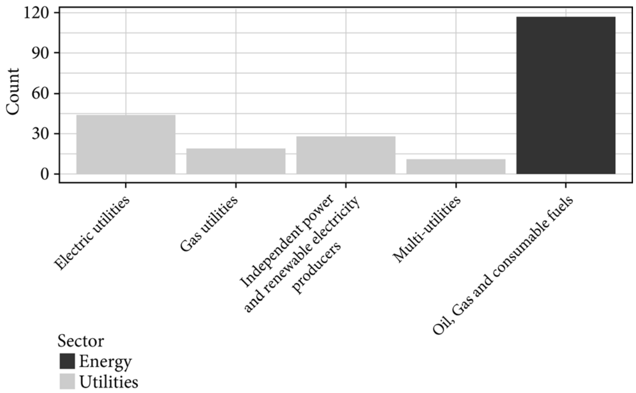

Table A1
Variable references

Variable	Dataset	Reference	Definition	Unit
Transition risk variables				
Scope 1	Trucost	Carbon-Scope 1	GHG emissions from operations that are owned or controlled by the company	Tons CO_2e
Scope 3	Trucost	Carbon-Scope 3	Other indirect GHG emissions not covered in Scope 2	Tons CO_2e
GWh gas	Trucost	Natural gas power generation	Total annual natural gas-based power generation	GWh
GWh coal	Trucost	Coal power generation	Total annual coal-based power generation	GWh
Reserves gas	Trucost	Reserves CO_2 emissions from Gas	GHG emissions embedded in oil reserves	Million tons CO_2
Reserves oil	Trucost	Reserves CO_2 emissions from Oil	GHG emissions embedded in gas reserves	Million tons CO_2
Capex oil & gas	Trucost	Capex Oil & Gas	Capital expenditure on oil & gas exploration (not disaggregated)	Million USD
Financial variables				
Dependent variable				
COD	Orbis			
		INTE/LTDB	Interest paid/long-term financial debts (e.g., to credit institutions (loans and credits), bonds)	%
Control variables				
Size	Orbis	TOAS	Total assets (fixed assets + current assets)	MUSD
Leverage	Orbis	LTDB/TOAS	Long-term financial debts (e.g., to credit institutions, loans and credits, bonds)/total assets (fixed assets + current assets)	%
Return on assets	Orbis	ROA	(Net income/total assets)	%
Interest coverage	Orbis	IC	All operating revenues - all operating expenses (gross profit-Other operating expenses)/all financial expenses such as interest charges, write-off financial assets, or total amount of interest charges paid for shares or loans	%
Liquidity ratio	Orbis	CURR	Current assets/current liabilities	%
Market/book ratio	Orbis	MCAP/TOAS	Market capitalization/total assets	%