The Climate Price Tag

Climate risk in sovereign bond yields and credit ratings

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M.Sc. Thesis

Stockholm School of Economics

2026

Abstract:
This thesis examines whether climate risks are reflected in government bond yields and sovereign credit ratings. Using a panel dataset of 80 advanced and emerging/developing countries over the period 2010–2023, we study seven climate-related variables capturing both transition climate risk and physical climate risk. We estimate two-way fixed-effects regressions to identify determinants of within-country variation over time. We separate effects across country groups, and we examine whether the Paris Agreement of 2015 marked a shift in the incorporation of climate risk. We also compare yield regressions with and without credit ratings as a control variable to assess whether sovereign credit ratings act as a transmission channel between climate risk and borrowing costs. Our results show that climate risk is increasingly reflected in sovereign finance, but unevenly across risk types, country groups, and transmission channels. Renewable energy consumption and participation in international climate treaties are most consistently associated with lower government bond yields, particularly after the Paris Agreement. By contrast, carbon intensity and fossil fuel rents show limited direct pricing in yields but become more strongly associated with lower credit ratings in the post-Paris period. For physical climate risk, temperature change appears to affect advanced country yields partly through credit ratings, while climate disaster frequency shows more direct post-Paris pricing in yields. Overall, our findings suggest that both markets and rating agencies have increasingly incorporated certain climate risks, although this incorporation varies across countries, risk types, and transmission channels.

Keywords:
Sovereign bond yield, Credit rating, Climate, Transition risk, Physical risk

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Acknowledgements:
We would like to express our appreciation and gratitude to our supervisor, Gualtiero Azzalini, for his support throughout the writing process.

M.Sc. Thesis
M.Sc. Program in Finance
Stockholm School of Economics

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1 Introduction

This thesis contributes to the growing strand of literature that seeks to untangle the relationship between climate risks on the one hand, and financial risks and returns on the other. This relationship has already been explored in several financial contexts, such as equities (Bolton & Kacperczyk, 2021), corporate bonds (Allman, 2022), asset values (Hong et al., 2019), government bonds (Kling et al., 2025; Cheng et al., 2023; Collender et al., 2023; Anyfantaki et al., 2025), and sovereign credit ratings (Cappiello et al., 2025; Klusak et al., 2023). It is to the last two niches — government bonds and credit ratings — that we make our contribution.

The climate-economy nexus is, of course, flooded with uncertainty. There is uncertainty about the future path of economic activity, about the future evolution of the climate, and about the interaction between the climate and the economy, with each source of uncertainty impacting prices and risk premia. We do not seek to uncover any of these paths in full. Studying the role of climate risks in government bond yields and in sovereign credit ratings does, however, shed light on an important, albeit limited, corner of the field that is worth understanding. After all, government bond yields and sovereign credit ratings both reflect and influence the real economy, making them of interest to governments and investors alike. Governments must understand what determines their cost of borrowing, since that cost constrains their room to manoeuvre. Investors, on their part, have an interest in understanding the pricing dynamics of one of the world's largest asset classes, one that is fundamental to the international financial system and serves as the starting point for most asset and security valuation, including corporate bonds for which government bonds represent the baseline. Sovereign credit ratings, lastly, play an important role in financial markets as they indicate the ability and willingness of sovereigns to service their debt, thereby guiding investment decisions and shaping demand for government bonds, while also serving as reference points in the policies of governments, regulators, and central banks.

Even our limited corner of the climate-economy nexus is challenging to untangle. There are many types of climate risk, and interactions between different climate risks are frequent. Most such risks, however, can be sorted into one of two main categories: physical climate risk and transition climate risk. The former is usually defined as risk arising from weather-related events with direct impacts. The latter refers to risk associated with the coming transition from a high-carbon economy to a low-carbon economy, which could involve, for example, new climate regulation, technological shifts, and changes in consumers' tastes and preferences towards more sustainable products and services. Naturally, a climate transition may bring both positive and negative economic impacts, which is why it is important to consider transition opportunities alongside transition risks. All transition-related variables studied in this analysis ultimately involve a trade-off between costs and benefits.

The transmission channels connecting climate risks to public finances and sovereign creditworthiness are also numerous and often interdependent. For example, a climate disaster can have direct fiscal impacts in the form of emergency aid and disaster reconstruction, as well as prolonged impacts through weakened infrastructure, disrupted supply chains, and reduced industrial competitiveness, or increased required investments in adaptation and mitigation. These impacts may, in turn, alter market participants' expectations regarding the affected country's future transition path, and so the disaster comes to shape transition risks as well. Meanwhile, the ambition to transition towards a more sustainable low-carbon economy may involve a re-allocation of resources from productive but unsustainable investments (that become stranded assets) to sustainable but less productive technologies, thereby reducing the country's income. Through channels such as these, climate risks are likely to influence government bond yields and sovereign creditworthiness.

The role of sovereign credit ratings in the climate-economy nexus has received little attention. Should credit ratings have a role in this context? According to the credit rating agencies, the answer is yes; Standard & Poor's (S&P), Moody's, and Fitch have all published documents, criteria and guidelines to affirm their recognition of environmental factors (Appendix 1). Yet, it is difficult to establish if they actually account for climate risks, and if so to what extent. These questions remain largely unanswered in the literature, with Cappiello et al. (2025) offering the most recent contribution.

Thus, the relationships between climate risks and government bond yields, and climate risks and sovereign credit ratings, need to be studied further. Not only that, these two niches should be bridged since sovereign credit ratings exert an influence on government bond yields (Afonso et al., 2015). What is incorporated in sovereign credit ratings may therefore be transmitted to government bond yields, with or without markets' understanding of this transmission channel. One of the aims of this study is to investigate if pricing of climate risk is transmitted in this way.

We conduct our study using a panel dataset of 80 countries, categorised as either advanced or emerging/developing. Analysing not only the full sample, but also the advanced and emerging/developing subsamples, is crucial as previous studies have uncovered marked differences between the two groups in the incorporation of certain climate risks in government bond yields (e.g. Collender et al., 2023) as well as sovereign credit ratings (Cappiello et al., 2025).

Our study covers the period 2010–2023. Crucially, and in line with some of the previous studies in the field, we treat the Paris Agreement as an exogenous event that may have altered the role of climate risks in government bond yields and sovereign credit ratings. The agreement was signed by 196 countries in December of 2015 and likely raised public awareness of the threat posed by climate change and the urgency of policy actions. For this reason, it is likely that climate risks were reassessed by market participants and credit rating agencies, either around the time of the agreement or later in the post-Paris period. Indeed, in May 2016 the major credit rating agencies signed the UN Principles for Responsible Investment (PRI), committing to systematically and transparently evaluate the extent to which environmental factors are relevant to credit assessments.

1.1 Findings

Our results show that transition risk is increasingly reflected in sovereign bond markets, though the extent and timing of this pricing vary considerably across risk types and country groups. Despite representing clear transition risks, higher CO_2 emissions relative to GDP and greater reliance on fossil fuel rents appear to carry limited risk premia in sovereign bond markets. In the post-Paris period, however, we see rating agencies increasingly associating higher carbon intensity and greater fossil fuel income dependency with lower sovereign credit ratings. This hints at a potential indirect impact on yields through credit ratings, though our models do not allow us to confirm this transmission story with confidence. This pattern is also confirmed by the Sustainable Development Index (reversed), a variable which we use as a proxy for overall transition risk — it shows limited evidence of a direct yield effect, but a significant post-Paris Agreement relationship in the credit rating models.

Among our transition risk variables, the share of renewable energy in a country's total energy consumption shows the most consistent direct pricing in government bond yields. It is negatively associated with yields across specifications, with the relationship strengthening slightly in the post-Paris period. Treaty participation, measured as the cumulative number of environmental treaties and conventions which a country has signed, tells a similar story. While its effect on yields appears to have been weak prior to the Paris Agreement, we identify a significant change in the period that followed, suggesting that markets increasingly began to appreciate treaty engagement.

For physical climate risks, the results are also mixed. Temperature change, measured as the annual deviation from a country's baseline temperature, shows limited direct pricing in government bond yields. However, a more nuanced picture emerges in the post-Paris period for advanced countries. Here, we control for credit ratings, temperature change has no significant effect on yields. When we remove the credit rating control, it does. This is suggestive of a transmission story — temperature change may reach government bond yields indirectly, through credit ratings. This is supported by our credit rating regression models showing that post-Paris, temperature increases were increasingly associated with lower credit ratings in advanced countries.

Disaster frequency, measured as the total number of climate-related disasters recorded by a country in a given year, presents a more direct pattern. It shows increased pricing in government bond yields following the Paris Agreement, while incorporation in credit ratings seems to have remained limited.

1.2 Contribution

This thesis makes several contributions to the existing literature. Most distinctively, we study government bond yields and sovereign credit ratings in parallel, allowing us to investigate the potential transmission channel between them, an aspect that has received limited attention in prior work. While previous studies have examined government bond yields and sovereign credit ratings in isolation, we explicitly tackle the question of whether the incorporation of climate risk in ratings is transmitted to yields by running regressions of ratings and by comparing regressions of yields with and without a credit rating control.

Second, our dataset covers 80 countries over the years 2010–2023, and therefore offers broader coverage and greater recency than most comparable studies. This allows us to study the post-Paris period more comprehensively, and to compare results across advanced, emerging, and developing countries. While some previous studies have explored whether the Paris Agreement changed how climate risk is priced, these focus on government bond yields or sovereign ratings in isolation, and use data that does not extend into the most recent years. By studying both dimensions through 2023, we find ourselves better placed to assess how the pricing of climate risk has evolved following the agreement, and whether this evolution has played out differently across country groups.

2 Background

Kling et al. (2018) were one of the first to study the relationship between climate risk and government bond yields. In 2025, an updated version of their paper was published in which they expanded their analysis and complemented it with additional robustness tests (Kling et al., 2025). The findings presented in both papers are, however, the same. Studying 46 countries, most emerging or developing, over the years 1996–2016, Kling et al. (2025) find that after controlling for macroeconomic and fiscal factors, climate vulnerability is positively related to government bond yields. They also find that social preparedness can mitigate this impact. As measures for climate vulnerability and social preparedness, Kling et al. (2025) use subcomponents of the Notre Dame Global Adaptation Initiative index (ND-GAIN). These subcomponents are broad and by construction correlated with important non-climate factors. The preparedness variable, for example, reflects investments in education, innovation, social equality, and ICT infrastructure. In the 2025 version of the paper, Kling et al. (2025) address endogeneity concerns by using, for example, principal component analysis and a modified vulnerability index, and show that their findings are robust. They also find a positive relationship between increases in a country's temperature and its government bond yields.

A similar study was conducted by Boitan & Marchewka-Bartkowiak (2022). However, instead of focusing on emerging and developing countries, they exclusively study EU countries over the period 2000–2020. Like Kling et al. (2025), Boitan & Marchewka-Bartkowiak (2022) find a positive relationship between climate vulnerability indices and government bond yields, and a negative relationship between climate risk readiness indices and government bond yields.

Böhm (2022) studies the relationship between temperature change and sovereign bond performance in emerging and developing economies — represented by the Emerging Market Bond Index (EMBI). Using data for 54 countries over the years 1994–2018, he finds that rising temperatures have a detrimental effect on sovereign bond performance. He finds this effect to be stronger in warm countries with low seasonality, and that independently of a country's climate, it can be mitigated by strong institutions that increase resilience towards temperature shocks. On the other hand, Böhm (2022) does not find that this relationship strengthened following the Paris Agreement, which he sees as an indication that it is the materialised economic effects of temperature change that are priced in government bonds, rather than markets' conception of future economic impacts (which may have changed following the agreement).

Cheng et al. (2023) study the pricing of transition risk in the 10-year government bond yields of 25 countries over the years 1995–2018. They use two transition risk variables: CO_2 emissions to GDP and a reversed Sustainable Development Index score. The latter is based on the Sustainable Development Index (SDI) developed by Hickel (2020), which measures the ecological efficiency of human development by dividing each country's human development score (life expectancy, education, income) by its 'ecological overshoot'. Cheng et al. (2023) reverse each country's SDI score to let 'unsustainable development' represent transition risk. Both transition risk variables show strong results, indicating that transition risk was incorporated into government bond yields during the studied time period. Interestingly, Cheng et al. (2023) also find that this pricing of climate risk can be eliminated by a country's implementation of green financial policies, which they believe serve as an effective tool to ensure a relatively smooth climate transition.

In a similar study, Collender et al. (2023) analyse the pricing of transition risk in 10-year government bond yields and yield spreads. Their dataset consists of 39 countries, divided into subsamples of advanced and emerging/developing countries, and covers the period 1999–2021. Collender et al. (2023) use three measures of transition risk: CO_2 per capita (carbon intensity), the share of renewable energy in total energy consumption, and the share of natural resource rents in total GDP. Their results show that while higher carbon intensity is associated with higher yields in advanced and emerging/developing countries alike, the pricing dynamics of the two other transition risk variables differ significantly between the two subsamples. While lower resource rents and a larger share of renewable energy consumption are associated with lower yields in advanced countries — presumably because they entail lower transition risk — the opposite is true in emerging and developing countries. Collender et al. (2023) explain these latter results by referring to the opportunity cost of transition. For many emerging and developing countries, they argue, transition effort is likely to be more costly, both because they are often financially constrained and because they tend to be rich in natural resources that can be capitalised on without large new investments. From the perspective of government bond investors, transitioning to renewable energy and away from fossil fuel income may therefore appear economically unattractive.

Anghel et al. (2025) conduct a comprehensive analysis of the interplay between climate risk and government bond yields and spreads. Their dataset contains 102 countries and covers the years 1980–2020. Their climate variables reflect both physical and transition risk. The former category is represented by the frequency of natural disasters, while the latter category is represented by CO_2

emissions, scaled either by GDP or by population. Anghel et al. (2025) also study the effects of certain political measures, such as environmental taxes, expenditure on environmental protection, and participation in international climate treaties and conventions. In their full sample, they find clear evidence of transition risk (CO_2 to GDP) being priced in government bond yields. They also find that the political measures studied have an impact on yields. Treaty participation, for example, is associated with lower yields, corroborating the findings of Saxena & Singh (2024) described below. However, Anghel et al. (2025) do not find evidence of climate disasters being priced in government bond yields. On the contrary, they find a consistently negative relationship between climate disaster frequency and yields, for which they fail to come up with a plausible explanation.

Like Anghel et al. (2025), Saxena & Singh (2024) also study the effect on government bond yields of governments participating in international environmental treaties and conventions. They hypothesise that two conflicting channels may enter into play when a country does so: the 'risk channel' and the 'incentive channel'. The first channel reflects the costs that may be brought about by a country's signing of a treaty, raising yields. The second channel, instead, is driven by the will of climate-conscious investors to provide a reward — in the form of lower yields — to participating countries, as a means of facilitating cost-sharing and mitigating the climate free rider problem amongst countries. By employing a difference-in-differences method focused on the signings of the Kyoto Protocol and the Paris Agreement, Saxena & Singh (2024) find support for the presence of the incentive channel.

In a recent working paper, Anyfantaki et al. (2025) also set out to study the pricing of both physical and transition risk in 10-year government bond yields. They use a dataset covering 52 countries over the years 2000–2023 to run panel regressions, as well as local projections to further analyse the effects of certain types of climate disasters. Regarding transition risk — in the form of CO_2 per capita — Anyfantaki et al. (2025) find strong evidence of pricing in yields, with the effect being more pronounced for emerging and developing countries than for advanced countries. Considering the results of Cheng et al. (2023), they hypothesise that the difference in results across subsamples may be due to advanced countries having implemented more green financial policies, thereby diminishing the risk associated with climate transition. Anyfantaki et al. (2025) also find evidence of increased pricing of transition risk amongst high-emitting countries following the Paris Agreement, suggesting that markets indeed attached greater importance to transition risk in this period. With respect to physical risk, they find no indication of temperature change being incorporated in government bond yields. Neither do they find evidence of climate disasters being systematically incorporated into government bond yields, although they see signs of such an effect when looking at countries with high public debt.

In another recent working paper, Cappiello et al. (2025) comprehensively study the incorporation of climate risks in sovereign credit ratings. Their analysis is based on a dataset that includes the ratings of four leading credit rating agencies, physical and climate risk variables, control variables, and several country group subsamples. The dataset includes 124 countries in total and covers the years 1999–2021. Cappiello et al. (2025) find clear differences in incorporation between physical risks and transition risks. The former category, represented both by temperature anomalies and climate disaster frequency, shows a clear negative relationship with credit ratings over the whole period. In their subsample analyses, they find that the effect of temperature anomalies on credit ratings is more pronounced in advanced countries, whereas the effect of natural disasters is greater for emerging countries. As for transition risk, Cappiello et al. (2025) instead find that variables such as carbon intensity were initially not incorporated by rating agencies, but that this changed in the post-Paris period.

Klusak et al. (2023) provide another interesting study on the relationship between climate risk and sovereign credit ratings, although it is methodologically different. By combining some of the leading climate-economy models with a self-developed random forests model, which predicts sovereign credit ratings using macroeconomic inputs, Klusak et al. (2023) simulate the effect of climate change on ratings under various scenarios. Even though the climate-economy models which they use mainly capture the losses of physical impacts, rather than transition costs, Klusak et al. (2023) find evidence of climate-induced sovereign downgrades as early as 2030 (their earliest simulation), increasing in intensity and spreading across more countries over the century. On the other hand, they also find that if global warming is limited to below two degrees Celsius, the impacts on sovereign credit ratings will be minimal.

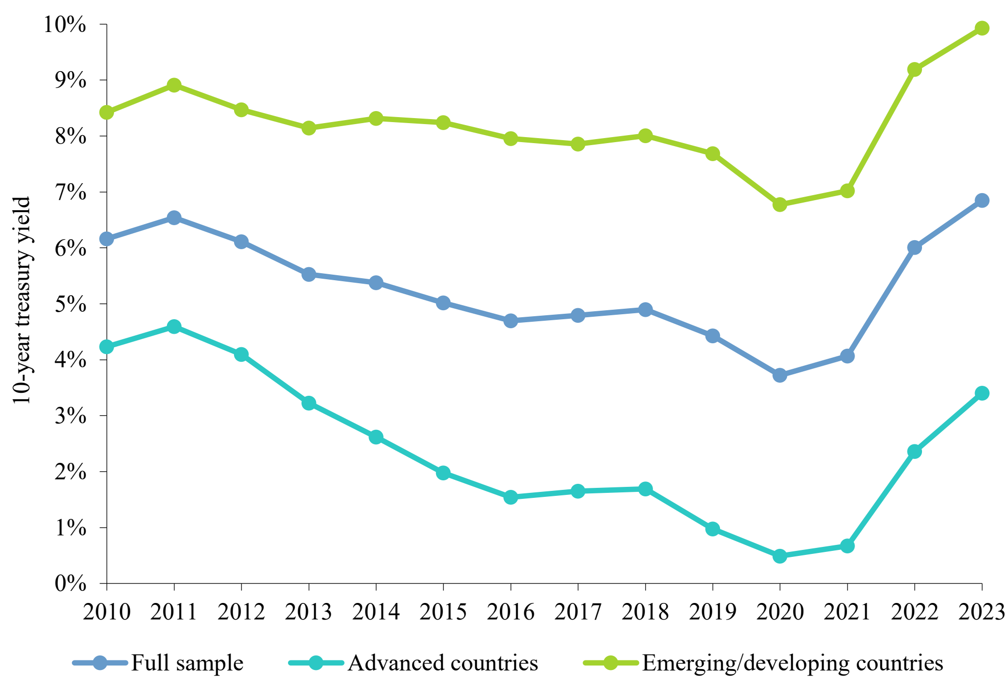
3 Data

We construct a panel dataset of country-year observations covering 80 countries over the period 2010–2023. The time window is chosen to reflect the recent period most relevant to contemporary climate policy, including the years around the Paris Agreement in 2015. Of the 80 countries in our dataset, 35 are classified as advanced in the World Economic Outlook database, while the remaining 45 countries are classified as either emerging or developing. We apply this country classification to the dataset to create an advanced and an emerging/developing subsample. A full list of the countries included in the dataset is provided in Appendix 2, and a complete overview of all variables, their sources, and any transformations applied is provided in Appendix 3. It should be noted that our panel is unbalanced, and that some of our climate variables do not have full coverage in the most recent end of our sample period.

3.1 Dependent variables

The main dependent variable in our analysis is the 10-year government bond yield. Our use of the 10-year maturity is motivated both by theory and by practical considerations. First, most climate risks are medium- to long-term risks, hence if they are priced in government bond yields it is most likely to show in longer maturities. Second, the 10-year maturity is the one most used in the literature (Kling et al., 2025; Cheng et al., 2023; Collender et al., 2023; Anyfantaki et al., 2025), ensuring maximum comparability of results. We construct the dependent variable by taking yearly averages of monthly data points, which we collect from the LSEG Workspace database. In the same fashion we calculate the yearly average yields of 5-year government bonds, which we use as a robustness check. Figure 1 shows the development of average 10-year government bond yields over the years 2010–2023. As can be seen, yields are significantly lower in the advanced subsample than in the emerging/developing subsample. Yet, the yields in the two groups display very similar development trends over time, highlighting the high level of global interconnectedness and dependency in modern economies and markets.

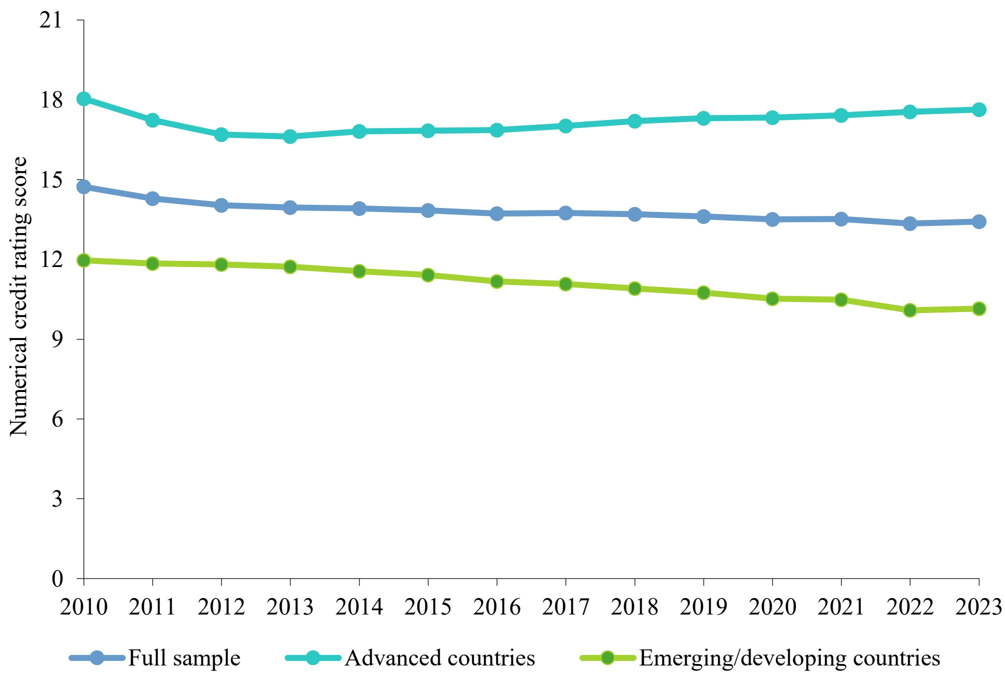
Figure 1: Average 10-year treasury yield, % (2010–2023)



Although yearly average yields are slightly right-skewed, we opt against a log transformation as the skewness is modest and often economically meaningful, representing for example the elevated level of risk in certain emerging and developing countries. Additionally, we value economic interpretability over symmetry — without log-transforming yields, the coefficients in our regression analyses correspond to basis points changes rather than percentage changes in yields. We also use country- and time-fixed effects, meaning that cross-sectional asymmetry does not affect our results. The choice of not log-transforming yields is consistent with much of the previous literature in the field. However, in our robustness section we re-estimate all specifications using a winsorised version of the 10-year government bond yields to see if our results are driven by outlier observations.

Our second dependent variable represents each government's credit rating. More precisely, we use the long-term issuer ratings provided by S&P, Moody's, and Fitch, which we turn into a numeric variable following the same procedure as Cappiello et al. (2025). This procedure involves mapping the credit rating agencies' letter grades onto a 1-21 scale (see conversion table in Appendix 4) and computing the variable by averaging across rating agency scores. Incomplete rating agency coverage is handled by averaging across the ratings available. Ratings are carried forward in time until changed. If a rating agency changes a country's rating multiple times in a single year, we use the last rating set for that year. Figure 2 shows the development of average full sample and subsample credit ratings over time. As illustrated, credit ratings are less volatile than government bond yields. It is interesting to note that the two subsamples show diverging trends from 2012 and onwards; advanced countries have, on average, improved their credit ratings while the opposite is true for emerging and developing countries.

Figure 2: Average sovereign credit rating, 1-21 scale (2010–2023)



3.2 Climate variables

Our analysis includes seven climate risk variables, five representing transition risk and two representing physical risk. All climate risk variables have, to varying degrees, been used in previous studies in the field, ensuring broad comparability of results. The use of each transition risk variable is motivated by a distinct assumption about how the climate transition will unfold and what costs it will bring with it, representing the multidimensional nature of climate transition. In other words, each transition risk variable is intended to capture a different aspect of transition risk, the only exception being the reversed SDI which is a broader index measure. The two physical risk variables represent chronic and acute physical risk.

Like several previous studies, we include a measure representing the carbon intensity of a country's economy. In our case, that measure is CO_2 emissions relative to GDP (we use CO_2 per capita as a test of robustness). An economy's carbon intensity is assumed to be indicative of the transition effort that remains and the costs which will have to be incurred in the process, with implications for public finance. Data for the variable is sourced from Our World in Data.

The two transition risk variables that follow are motivated by the assumption that the climate transition will involve a large-scale shift towards renewable energy sources — and they are both used by Collender et al. (2023), with whom we compare our results. The first of these is the proportion of renewable energy in a country's total energy consumption. The second is oil, gas, and coal rents to GDP (transformed by taking the square root). Thus, while both variables are based on the same fundamental assumption, one reflects the sustainability of a country's energy consumption while the other reflects an unsustainable component of a country's income. In consequence, a higher proportion of renewable energy consumption, and a lower dependency on oil, gas, and coal rents, indicate a smoother, less substantial, and less costly climate transition to come. Data for these variables are sourced from the World Bank.

Following Anghel et al. (2025), we include a variable for environmental treaty participation. This variable reflects the number of international environmental treaties and conventions which a country has signed up to and including a given year. A country's adherence to treaties and conventions can, potentially, shape its exposure to transition risks and transition opportunities in more ways than one. For example, if a country increases the scope of its climate transition it should, all else equal, also increase the costs associated with that transition. A commitment to simply accelerate the climate transition, all else equal, may be interpreted favourably or unfavourably depending on how the attractiveness of quickly reducing transition risk compares to the opportunity costs of forgoing certain — non-transition-compatible — activities. Additionally, climate treaties and conventions may shape how countries transition, with due economic consequences. Participation in treaties and conventions may also constitute a credible signal of a government's policy ambition, which in turn may, as Saxena & Singh (2024) write, be rewarded by climate-conscious investors as they seek to mitigate the climate free rider problem amongst countries. Data on treaty participation is sourced from the United Nations Statistics Division.

To further confirm the validity of the previous variables as transition risk variables, we also include an index variable closely tied to transition risk, namely the SDI developed by Hickel (2020). This index measures the ecological efficiency of human development by dividing each country's human development score (life expectancy, education, income) by its ecological overshoot, described by Hickel (2020) as the extent to which consumption-based CO_2 emissions and material footprint exceed fair shares of planetary boundaries. Assuming that such planetary boundaries will have to be respected in the future (or at least more so than in the recent past), the SDI contains a clear transition risk component, why we compare results for the variable with those of the other transition risk variables. Like Cheng et al. (2023), we reverse the SDI so that higher values indicate greater ecological overshoot and thus higher transition risk.

To represent chronic physical risk, we employ a temperature change variable corresponding to the annual temperature change relative to the 1951–1980 baseline. Temperature change is a widely used proxy for chronic physical risk in the literature (Anyfantaki et al., 2025; Böhm, 2022; Collender et al., 2023; Cappiello et al., 2025) as it captures the gradual and persistent shifts in climatic conditions that affect economic activity through channels such as agricultural productivity, labour efficiency, energy demand, and long-term capital depreciation (Dell et al., 2012; Burke et al., 2015). Unlike more volatile environmental indicators, temperature tends to evolve smoothly over time and is therefore well suited to capturing the slow-moving nature of chronic risk. We construct this variable using data from the World Bank.

We let climate disaster frequency represent acute physical climate risk. For our data, we draw on the Emergency Events Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at UCLouvain. Like Anyfantaki et al. (2025) and Anghel et al. (2025), we filter our data to include only climate-related natural disasters (floods, storms, extreme temperatures, droughts, landslides, and wildfires), excluding non-natural events such as epidemics and infestations. Frequency is measured as the total number of qualifying disaster events recorded by a country in a given year. Climate disaster frequency provides a direct and observable proxy for acute risk, reflecting the realisation of high-impact, low-probability events that can cause immediate disruptions to economic activity, infrastructure, and financial systems. Importantly, climate change is expected to increase both the frequency and severity of extreme weather events, with disruptions likely to intensify over time, particularly in warmer countries where heat-related disasters already show stronger impacts on economic performance (Böhm, 2022).

Table 1 reports summary statistics for the dependent and explanatory variables across all country groups.

Table 1: Dependent and climate variable summary statistics

	N	Mean	Min	Max	Std	Within Std
All countries						
10y yield	951	5.28	-0.52	33.92	4.68	1.94
5y yield	980	4.80	-0.79	61.15	5.36	3.00
CreditRating	1099	13.81	1.67	21.00	4.94	1.13
CO_2/GDP	1040	0.24	0.06	0.77	0.13	0.03
RenewableEnergy	938	26.24	0.00	93.60	22.58	2.79
OilGasCoalRents	941	2.33	0.00	50.15	5.82	1.93
TreatyParticipation	1050	12.97	6.00	14.00	1.19	0.57
SDIReversed	1027	0.44	0.16	0.95	0.21	0.04
TemperatureChange	1036	1.21	-0.76	3.49	0.64	0.47
DisasterFrequency	1120	2.85	0.00	43.00	4.68	2.12
Advanced						
10y yield	478	2.39	-0.52	25.48	2.34	1.84
5y yield	483	2.01	-0.79	61.15	4.47	3.65
CreditRating	490	17.18	2.67	21.00	4.06	1.09
CO_2/GDP	455	0.21	0.06	0.43	0.08	0.03
RenewableEnergy	396	21.52	0.50	82.90	17.41	2.52
OilGasCoalRents	408	0.46	0.00	10.01	1.30	0.42
TreatyParticipation	462	12.99	6.00	14.00	1.44	0.58
SDIReversed	442	0.55	0.18	0.92	0.20	0.05
TemperatureChange	462	1.39	-0.76	3.09	0.68	0.57
DisasterFrequency	490	2.20	0.00	43.00	4.43	1.62
Emerging/Developing						
10y yield	473	8.20	0.00	33.92	4.65	2.04
5y yield	497	7.51	0.06	33.60	4.73	2.20
CreditRating	609	11.09	1.67	19.00	3.76	1.16
CO_2/GDP	585	0.26	0.06	0.77	0.16	0.04
RenewableEnergy	542	29.70	0.00	93.60	25.17	2.97
OilGasCoalRents	533	3.76	0.00	50.15	7.33	2.53
TreatyParticipation	588	12.95	10.00	14.00	0.95	0.55
SDIReversed	585	0.35	0.16	0.95	0.17	0.03
TemperatureChange	574	1.07	-0.26	3.49	0.56	0.38
DisasterFrequency	630	3.37	0.00	34.00	4.82	2.44

3.3 Control variables

Our control variables for the regressions of government bond yields are drawn from the established literature on their determinants. We include real GDP growth to control for the size and economic strength of a country's economy (González-Fernández & González-Velasco, 2018), as higher growth rates signal a greater ability to service debt and are therefore expected to be associated with lower yields (Broeders et al., 2022). Inflation is included as a winsorised consumer price index. While its overall impact on yields is theoretically ambiguous, high inflation increases macroeconomic uncertainty and is generally expected to raise borrowing costs (Boitan & Marchewka-Bartkowiak, 2022). To control for fiscal strength, we include gross government debt as a percentage of GDP and the government primary surplus as a percentage of GDP. We also include the current account balance as a percentage of GDP, as persistent current account deficits can signal external vulnerabilities and increase sovereign risk perceptions (De Haan et al., 2014; Broeders et al., 2022). Trade openness, measured as total trade as a percentage of GDP, is included as it is key to a country's external solvency. While higher trade openness may improve a country's ability to refinance debt through future trade surpluses, it can equally signal that such surpluses are required to meet foreign debt repayments (Collender et al., 2023). To account for exchange rate dynamics, we include the exchange rate relative to the US Dollar, sourced from the Bank for International Settlements. Finally, we include a measure of government effectiveness to account for institutional quality. Countries with stronger institutions are better positioned to manage fiscal pressures, making institutional quality an important determinant of sovereign borrowing costs (Cevik & Jalles, 2024). All the above variables are sourced from the World Bank and the IMF unless otherwise stated.

Sovereign credit ratings are included as a control variable in our baseline specifications as they aggregate a broad set of risk characteristics and carry statistically significant effects on bond prices (Afonso et al., 2015). However, including credit ratings as a control in our baseline specifications reduces the marginal significance of certain other controls, such as government effectiveness, since credit ratings partly reflect the same underlying information. This is not an issue since we only intend to analyse the effects of our selected climate variables.

The control variables for our credit rating regressions closely follow the framework established by Cantor & Packer (1996), which remains an important reference in the sovereign ratings literature. We include GDP per capita, as wealthier countries generally have greater fiscal capacity and are assessed more favourably by rating agencies. Real GDP growth is included as a forward-looking signal of debt sustainability, with higher growth expected to be associated with better ratings. Inflation (winsorised) captures macroeconomic stability — persistently high inflation is typically viewed negatively by rating agencies as it erodes fiscal credibility. Gross government debt as a percentage of GDP is included as a direct measure of fiscal burden, with higher debt expected to be associated with lower ratings. The current account balance as a percentage of GDP is included to capture external vulnerabilities, as sustained deficits can signal dependence on foreign financing and increase default risk perceptions. We also include government effectiveness to account for institutional quality, reflecting the view that strong institutions enhance a government's ability to implement sound fiscal policy and respond to economic shocks. Finally, we include a self-constructed debt-in-default dummy variable, which takes the value of one if a country has any sovereign debt in default in a given year, following the approach of Cappiello et al. (2025). This variable is constructed using data from the BoC-BoE Sovereign Default Database.

4 Methodology

4.1 Regression model considerations

Throughout the regression models, we consistently lag all control variables by one year to mitigate concerns regarding simultaneity and reverse causality. After all, changes in government bond yields and credit ratings are likely to feed back into a country's fiscal position as well as broader macroeconomic conditions.

By contrast, climate variables are entered contemporaneously. These variables, we believe, are less susceptible to reverse causality and are intended to capture the updated information available to market participants when pricing government bond yields, and to rating agencies when setting credit ratings. This treatment is also common practice in the literature. It is true, however, that when it comes to our transition risk variables, a certain degree of reverse causality cannot be ruled out. After all, a country's financing conditions and borrowing costs may shape its climate transition through investment capacity and policy choices. These effects, however, likely only materialise over longer horizons.

Also common to all regression models is the application of country and time fixed effects. Thus, we explicitly analyse the determinants of within-country variation over time in our dependent variables. This is important to keep in mind when interpreting the effects of our climate variables; coefficients for our treaty participation variable, for example, should be interpreted as the effect of within-country increases in treaty participation, rather than cross-country differences in treatment engagement.

We cluster standard errors at the country level to allow for arbitrary correlation of errors within a country over time. This approach produces heteroskedasticity-robust standard errors and remains valid in the presence of an unbalanced panel such as ours.

4.2 Government bond yield regressions

Our first regression model fits one climate variable along with the relevant set of control variables, including the credit rating variable, and thus takes the following form:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\mathbf{X}_{i,t-1} + \lambda Credit\ rating_{i,t-1} + \epsilon_{i,t} \quad (1)$$

Y is the dependent variable, the annual average government bond yield. α and β represent the country and time fixed effects. X represents the set of control variables and ϵ is the error term. The coefficient of interest is γ, representing the effect of the climate variable.

4.3 Credit rating regressions and credit rating control

To investigate whether climate risks are incorporated into credit ratings, we run the following model:

$$R_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \ (2)$$

In Model 2, R represents the credit rating variable. α and β are the country and time fixed effects, and X represents the relevant set of control variables, described in section 3.3. ϵ is the error term. Also, here the coefficient of interest is γ, as it represents the effect of the climate variable.

Lastly, in order to understand if credit ratings transmit pricing of climate risks to government bond yields, we complement Model 1 and 2 with a modified version of the former where we remove the credit rating control variable. This model takes the following form:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \ (3)$$

If the results of a climate variable are sensitive to the inclusion of a credit rating control, it suggests that credit ratings act as a transmission channel for part of the climate risk, incorporating it into government bond yields. Controlling for credit ratings in Model 1 may therefore absorb that part of a climate variable's effect. By virtue of not including a credit rating control, Model 3 can capture both the direct and indirect, transmitted, effect of a climate variable with respect to government bond yields. Thus, the results of Model 1, 2, and 3 will not only allow us to assess the potential pricing of climate risks in government bond yields and their potential incorporation in credit ratings; a cross-model comparison of results will allow us to see if credit ratings act as a transmission channel for the pricing of climate risks to government bond yields.

4.4 Post-Paris analysis

To study the potential changes in the effects of our climate variables following the Paris Agreement, we add to Model 1 an interaction term with a post-Paris dummy variable. The model becomes:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + \lambda Credit\ rating_{i,t-1} + v\left(Climate\ variable_{i,t} * postParis_t\right) + \epsilon_{i,t} \ (4)$$

In this model, the coefficient of the interaction term, v, represents the change in the effect of the climate variable in the post-Paris period vis-à-vis its effect in the pre-Paris period, γ. The total effect of the climate variable in the post-Paris period therefore equals the sum of v and γ.

To examine the potential changes in incorporation of climate risk into credit ratings, we augment Model 2 with the post-Paris interaction term, resulting in:

$$R_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + v\left(Climate\ variable_{i,t} * postParis_t\right) + \epsilon_{i,t} \quad (5)$$

Also here, γ represents the effect of the climate variable in the pre-Paris period, v represents the change in effect associated with the post-Paris period, and the sum of γ and v, therefore, represents the effect of the variable in the post-Paris period.

Lastly, in order to glimpse the potential role of credit ratings as a transmission channel for the pricing of climate risk, we also run a modified version of Model 4 that does not include credit ratings as a control variable.

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + v\left(Climate\ variable_{i,t} * postParis_t\right) + \epsilon_{i,t} \quad (6)$$

Like Model 3, Model 6 is useful because its exclusion of the credit rating control allows it to capture both the direct and the indirect, transmitted, effect of the climate variable, if there is one.

4.5 Dynamic country group analyses

At certain points in our analysis, we find that a climate variable may have a non-linear effect on one of our dependent variables. Several such non-linear relationships have also been identified by previous studies (described in the background section). In such instances, we complement Models 1–6 with additional dummy variables based on dynamic country groups. These groups contain the countries that place above or below a certain percentile with respect to a particular climate variable. Examples include countries with a particularly high carbon intensity, or a particularly low consumption of renewable energy. The country groups are dynamic in the sense that they are recreated for each year in the dataset.

In the following models, the dummy variable corresponding to a dynamic country group is called the Group Dummy. We use it to distinguish the differential effects associated with a dynamic country group, both over the full 2010–2023 window and in the pre- and post-Paris periods.

Adding a Group Dummy interaction term to our initial regression of government bond yields, Model 1, gives us:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \rho(Climate\ variable_{i,t} * Group\ Dummy_{i,t}) + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + \lambda Credit\ rating_{i,t-1} + \epsilon_{i,t} \quad (7)$$

Here, γ represents the effect of the climate variable for countries not included in the dynamic country group. For countries included in that group, the effect of the climate variable corresponds to the sum of γ and ρ.

Adding a Group Dummy interaction term to our regression of government bond yields with a post-Paris dummy variable, Model 4, gives us:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \rho(Climate\ variable_{i,t} * Group\ Dummy_{i,t}) + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + \lambda Credit\ rating_{i,t-1} + v(Climate\ variable_{i,t} * postParis_t) + \phi(Climate\ variable_{i,t} * postParis_t * Group\ Dummy_{i,t}) + \epsilon_{i,t} \quad (8)$$

Here, γ represents the pre-Paris effect of the climate variable for countries not included in the dynamic country group. The pre-Paris effect of the climate variable for countries included in that group is represented by the sum of γ and ρ. For countries not included in the dynamic country group, the post-Paris change in effect is given by v, with the total effect in the post-Paris period corresponding to the sum of γ and v. For countries that are part of the dynamic country group, the post-Paris change in effect is given by the sum of v and ϕ, with the total effect of the climate variable in the post-Paris period corresponding to the sum of γ, ρ, v and ϕ.

Lastly, adding a Group Dummy interaction term to our regression of credit ratings which also includes a post-Paris dummy variable, Model 5, gives us:

$$R_{i,t} = \alpha_i + \beta_t + \gamma Climate\ variable_{i,t} + \rho(Climate\ variable_{i,t} * Group\ Dummy_{i,t}) + \boldsymbol{\delta}'\boldsymbol{X}_{i,t-1} + v(Climate\ variable_{i,t} * postParis_t) + \phi(Climate\ variable_{i,t} * postParis_t * Group\ Dummy_{i,t}) + \epsilon_{i,t} \quad (9)$$

As in Model 8, γ represents the pre-Paris effect of the climate variable for countries not included in the dynamic country group. The pre-Paris effect for countries included in that group is instead given by the sum of γ and ρ. For countries not included in the dynamic country group, the post-Paris change in effect is given by v, with the total effect in the post-Paris period equalling the sum of γ and v. For countries that are part of the dynamic country group, the post-Paris change in effect is the sum of v and ϕ, with the total effect in the post-Paris period corresponding to the sum of γ, ρ, v and ϕ.

4.6 Subsample analyses

After running Models 1–6 on our full sample, we repeat the analysis on our advanced and emerging/developing subsamples.

4.7 Limitations of methodology

An important feature of our methodology is comparing specifications with and without credit ratings as a control variable, which allows us to assess whether climate risks reach government bond yields through their prior incorporation in ratings. This comparison relies on several assumptions. First, we assume that credit ratings affect yields rather than the other way around —

we also mitigate concerns for reverse causality by lagging the credit rating control by one period. Second, we assume that no omitted third factor simultaneously drives both climate risk exposure and credit ratings in a way that would distort our results, in other words, that there is no omitted variable bias. Our fixed effects and relevant control variables help address this, but unobserved time-varying factors can never be fully ruled out.

Furthermore, although our treatment of the Paris Agreement as an exogenous turning point is standard in the literature, it comes with certain caveats. We assume that the agreement itself triggered a shift in how climate risk is perceived, rather than it simply representing a step in a gradual process that was underway already before 2015. We also assume that any post-Paris changes we observe can be attributed to the agreement, rather than to other developments happening at the same time, such as the rise of ESG investing and growing climate disclosure requirements.

Finally, the precision of our estimates is inherently limited by the combination of two-way fixed effects and the slow-moving nature of some of our climate variables. By including country and time fixed effects, our models identify effects using within-country variation over time. This requires the explanatory variables to have a sufficient degree of within-country variation. As illustrated in Table 1, such variation is modest for some slow-moving climate variables, such as CO_2 to GDP. Consequently, the estimates for these variables may be less precise, as the models have limited power to detect their effects even when they are economically relevant.

5. Results

Below we present the results for each climate variable, with the variables divided into two sections, one for transition risk and one for physical risk. Tables containing results figures are presented at the end of each section. Appendices 6 and 7 report the baseline regressions for Model 1 and Model 2 respectively, estimated without climate variables. The control variables explain a meaningful share of the variation in both dependent variables — R-squared values are modest, but this is expected in models where country and time fixed effects absorb a substantial share of total variation. For simplicity, control variable results are excluded from all subsequent regression tables.

5.1 Transition risk

5.1.1 CO_2 to GDP

Coefficients for the *CO_2/GDP* variable are statistically insignificant across all country samples in our basic yield regression (Model 1, Table 2). This stands in contrast to several previous studies (Cheng et al., 2023; Collender et al., 2023; Anghel et al., 2025; Anyfantaki et al., 2025), which may partly reflect our focus on the more recent 2010–2023 period, a timeframe in which the pricing of carbon intensity may have evolved in ways that earlier studies do not capture. Adding the post-Paris dummy (Model 4, Table 3) reveals consistently positive interaction terms, though only the one for the emerging/developing subsample shows weak significance. Thus, while we may be seeing hints of stronger pricing of carbon intensity post-Paris, as was found by Anyfantaki et al. (2025), clear evidence is lacking.

CO_2 to GDP shows similar dynamics in our credit ratings regressions. When looking at the basic ratings model (Model 2, Appendix 8), we see no indication of high carbon intensities being 'punished' by credit rating agencies and vice versa. However, the picture changes when we add the post-Paris interaction term (Model 5, Table 4). Here, interaction coefficients are negative and statistically significant for the full sample and the emerging/developing subsample. For the full sample, the post-Paris change in effect corresponds to a 0.37-notch decrease in credit rating per one-standard-deviation increase in CO_2 to GDP (the full effect in the post-Paris period, though not statistically significant, corresponds to a 0.67-notch decrease in credit rating per one-standard-deviation increase in CO_2 to GDP). This indicates that credit rating agencies attached greater importance to carbon intensity in the post-Paris period, consistent with Cappiello et al. (2025). These results suggest that while the direct pricing of carbon intensity in government bond yields is weak or limited, credit rating agencies appear to have begun focusing on a country's carbon intensity in the post-Paris period, potentially serving as a transmission channel projecting some of the associated risk onto government bond yields. That said, removing credit ratings as a control does not change the significance of the CO_2 to GDP coefficients in the yield regression (Model 6, Appendix 10), offering no direct support for the transmission channel hypothesis.

Since the post-Paris effect of carbon intensity on credit ratings is strong in the emerging/developing subsample (where we find the highest-emitting countries in our data), but absent in the advanced subsample, we suspect that credit rating agencies especially began to penalise countries with carbon intensities markedly above global standards. To test this suspicion, we create an additional dummy variable which we add to the analysis. The new dummy variable, called High Emitter, corresponds to a dynamic country group consisting of those countries whose CO_2 to GDP, in a given year, is above the 75^{th} percentile in the full sample. We use this dummy variable as the Group Dummy, combined with CO_2 to GDP as the Climate Variable (Model 9, Appendix 14). Our results show negative signs on the High Emitter interaction coefficients, suggesting that credit rating agencies may have applied particularly great penalties to the highest-emitting countries in the post-Paris period. However, the lack of statistical significance means that these results should only be treated as indicative.

5.1.2 Renewable energy

The results for the *RenewableEnergy* variable suggest that a country's consumption of renewable energy is significantly associated with its government bond yields, providing some of the most consistent evidence of direct transition risk pricing in our analysis. The results from running our basic yield model (Model 1, Table 2) show meaningful negative coefficients across samples, with the ones for the full and the emerging/developing samples being statistically significant. This indicates that a greater share of renewable energy in a country's energy consumption is associated with lower government bond yields. In the full sample of countries, an increase of one percentage point in the renewable share of total energy consumption corresponds to a decrease in yields of approximately 10 basis points. This suggests that the transition risk associated with the consumption of energy from unsustainable sources is priced by markets. Moreover, negative post-Paris interaction coefficients (Model 4, Table 3), statistically significant for the advanced and emerging/developing subsamples, indicate that this risk premium increased in the post-Paris period. For the emerging/developing subsample, where the post-Paris change in effect is the largest, the new total effect implies a decrease in yields of approximately 17 basis points per one-percentage-point increase in the share of renewable energy consumption.

Our results regarding the relationship between government bond yields and the consumption of renewable energy are only partly in line with what was found by Collender et al. (2023). In their study, Collender et al. (2023) found a positive relationship between the two — a greater share of renewables corresponding to higher costs of borrowing — when looking only at emerging and developing countries. They argued that this was due to the costs for building renewable energy sources being relatively high in these countries, making it an unattractive pursuit despite the reductions in transition risk which would follow. We believe that this divergence of results is, at least in part, due to a difference in time periods studied; while our sample window covers the years 2010–2023, Collender et al. (2023) use a dataset covering 1999–2021. The positive relationship which they found for emerging and developing countries may therefore gradually have shifted and changed sign, possibly driven by access to renewable energy becoming cheaper, and increased regulatory pressure and costs targeting non-renewable energy sources.

We also find suggestive evidence of a non-linear relationship between renewable energy consumption and government bond yields when employing dynamic country groups. Specifically, we create a Low Renewables dummy representing those countries whose share of renewable energy consumption, in a given year, places them below the 25th percentile in the full sample (Model 7, Appendix 15). Our results show that when regressing the full sample of yields on a standalone term and a Low Renewables interaction term, the two coefficients — both statistically significant — essentially cancel out. This could be due to the countries with the lowest consumption of renewable energy still facing high transition costs in this respect. The economic benefits of transition are, in other words, offset; for example, by high costs for accessing renewable energy, or by unusually low costs to access fossil energy. Collender et al. (2023) found this transition-cost effect to be dominant in their emerging/developing subsample, to the point where a positive relationship emerged between the consumption of renewable energy and government bond yields. In comparison, we find signs of the effect only when looking at a smaller group of low-renewables countries, and even then, it is not strong enough to create a positive renewables-yields relationship — it simply cancels out the negative relationship found in the full sample.

In contrast, renewable energy consumption shows no significant positive relationship with sovereign credit ratings, either before or after the Paris Agreement (Model 5, Table 4). This suggests that markets price renewable energy consumption directly, without credit ratings acting as a transmission channel. The lack of explicit references to renewable energy in the rating methodologies reviewed in Appendix 1 is consistent with this result. However, we do find a statistically significant negative relationship between renewable energy consumption and credit ratings in the emerging/developing subsample. Rather than reflecting a causal relationship, the negative coefficient may be due to changes in renewable energy consumption coinciding with important country-specific developments not fully captured by our controls.

5.1.3 Oil, gas & coal rents

In our basic yield specification (Model 1, Table 2), we see a negative relationship between the *OilGasCoalRents* variable and government bond yields across samples, with the coefficients for the full sample and the emerging/developing subsample being statistically significant. This could be explained by markets valuing the economic benefits resulting from these rents more than the reduction in transition risk that a decreased dependency on them would entail. In other words, the opportunity cost of transitioning away from oil, gas, and coal rents may be perceived as too high to make such a transition attractive. Collender et al. (2023) offer the same explanation, also finding a negative relationship between natural resource rents and government bond yields, though only in emerging and developing countries. For advanced countries, they instead find a clear positive relationship between rents and yields, indicative of transition risk. When adding a post-Paris dummy variable to our yield regressions (Model 4, Table 3), we find consistently positive interaction term coefficients, possibly hinting at a stronger pricing of the transition risk associated with oil, gas, and coal rents. However, these coefficients are not statistically significant.

Fossil fuel rents display similar effects and trends with respect to sovereign credit ratings, though the post-Paris trend appears stronger (Model 5, Table 4). Standalone coefficients lack statistical significance whereas the post-Paris interaction coefficients are statistically significant for full sample and the emerging/developing subsample and consistently negative (for these samples the total effect post-Paris also becomes negative, though not statistically significant). Thus, it seems that credit rating agencies increasingly began to account for the transition risk associated with the oil, coal, and gas industries following the Paris Agreement — more so than investors in government bonds. While it is likely that some of the rating agencies' consideration of this risk was transmitted to government bond yields through their ratings, removing credit ratings as a control in our post-Paris yield regressions does not uncover a greater effect (Model 6, Appendix 10).

5.1.4 Treaty participation

In contrast to the findings of Anghel et al. (2025) and Saxena and Singh (2024), our basic yield regression (Model 1, Table 2) does not reveal a negative relationship between *TreatyParticipation* and government bond yields. Instead, we find a weakly significant positive coefficient for the advanced subsample. However, this result should not be overinterpreted. During the pre-Paris period in our sample, very few additional treaties and conventions were signed by the advanced countries, meaning that the coefficient is based on very limited within-country variation and likely reflects a sample-specific artefact rather than a true underlying relationship.

Once again, a new trend emerges when we add a post-Paris interaction term (Model 4, Table 3). Here, participation in treaties shows meaningful and significant, negative, post-Paris interaction coefficients across the full sample and both subsamples, indicating that in the post-Paris period, a country's signing of international environmental treaties and conventions was increasingly perceived and acted upon by markets. While the variable's total post-Paris effect on yields is negative in the full sample and in the emerging/developing subsample, this effect does not reach statistical significance.

To understand whether the negative post-Paris interaction coefficients in Model 4 reflect a shift in the transition costs vs. transition benefits equation, as perceived by markets, or a strengthening of the 'incentive channel' hypothesised by Saxena & Singh (2024), we employ a dynamic High Emitter country group whose carbon intensity is above the 75^{th} percentile in the full sample. Saxena & Singh (2024) argued that countries with a high carbon intensity face a relatively worse transition costs vs. transition benefits equation (the costs being high and the benefits being low), and that climate-conscious investors, therefore, provide them with an extra incentive to participate in climate treaties and conventions in the form of lower government bond yields. By interacting the High Emitter dummy variable with treaty participation (Model 8, Appendix 16), we test if we can see signs of the incentive channel. The results of this regression, however, show that we do not; in the model, only the regular post-Paris interaction coefficient is statistically significant. Therefore, we find it more likely that the significant post-Paris change in effect which we find is explained by a change in the markets' perception of the costs and benefits associated with treaty participation and adherence — the former becoming lower and the latter becoming greater.

The post-Paris credit rating regression (Model 5, Table 4) tells a consistent story: credit rating agencies, like financial markets, became increasingly responsive to treaty participation after the Paris Agreement. The post-Paris interaction coefficients of the Treaty Participation variable are positive across samples, with the one for the advanced subsample being statistically significant. The model also shows a statistically significant, negative, standalone coefficient for the emerging/developing subsample. One possible explanation for this is that fossil resource-rich countries in this subsample tend to have high creditworthiness but low treaty participation, creating a negative correlation between treaty participation and credit ratings that our controls do not fully absorb.

5.1.5 SDI reversed

We use the *SDIReversed* variable as an initial robustness check as it captures multiple ecological-overshoot dimensions, and therefore functions both as a proxy for overall transition risk and as a test of the robustness of our findings so far.

In our basic yield regression, we find no evidence of a statistically significant effect of the reversed SDI on yields (Model 1, Table 2). This does not change when introducing a post-Paris interaction term (Model 4, Table 3), suggesting that the reversed SDI does not significantly capture a component of transition risk directly priced in government bond yields. Nevertheless, the coefficients of the reversed SDI are positive across all yield specifications, in line with the theoretical expectation that greater transition risk exposure is associated with higher borrowing costs.

Comparing these findings to the existing literature reveals discrepancies. Cheng et al. (2023) find that the variable is positively and significantly associated with government bond yields if green policy frameworks are absent. Introducing such frameworks, they find, renders the effect insignificant. Several explanations may account for this divergence. For example, differences in sample construction are likely to play an important role; Cheng et al. (2023) draw on data from 1995–2018 across just 25 countries, whereas our sample spans 2010–2023 across 80 countries, reflecting, amongst other things, a different policy environment.

The results of our post-Paris credit rating model (Model 5, Table 4) suggest that while the reversed SDI does not extensively reflect components which are strongly priced in yields, some of its components may be more accounted for in sovereign credit ratings (which in turn may transmit some such pricing to yields). The post-Paris interaction coefficient is statistically significant and negatively associated with credit ratings in both subsamples, consistent with the pattern observed for the previous transition risk variables.

In summary, while the reversed SDI does not significantly capture factors priced in government bond yields — not enough for the variable to show a relationship with yields on its own — it seems that credit rating agencies began to account for its components following the Paris Agreement. This interpretation is also supported by the qualitative criteria used by credit rating agencies (Appendix 1), which emphasise factors such as resource constraints and structural adjustment costs, dimensions closely related to what the reversed SDI captures. The results align with our findings for CO_2 to GDP and oil, gas, and coal rents, suggesting that carbon intensity and fossil fuel income dependency are important drivers of a country's ecological overshoot, and by extension of the transition risk which the reversed SDI reflects.

Table 2: Transition risk, yield regression (including credit rating as control)

OLS estimates from Model 1 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield All	Yield All	Yield All	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Eme	Yield Eme	Yield Eme	Yield Eme	Yield Eme
CO_2/GDP	0.717 (6.440)					6.181 (7.641)					-7.864 (6.732)				
RenewableEnergy		-0.101** (0.049)					-0.057 (0.066)					-0.122* (0.071)			
OilGasCoalRents			-1.044* (0.563)					-0.172 (0.761)					-1.557*** (0.590)		
TreatyParticipation				0.111 (0.244)					0.429* (0.257)					-0.280 (0.561)	
SDIReversed					5.729 (4.786)					4.769 (4.979)					5.012 (5.938)
Observations	659	602	602	702	659	374	343	343	405	374	285	259	259	297	285
R-squared within	-0.097	0.085	-0.147	-0.041	-0.215	0.408	0.381	0.321	0.081	0.270	-0.574	-0.156	-0.640	-0.018	-0.478
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Transition risk, yield regression (with credit rating control and post-Paris dummy)

OLS estimates from Model 4 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield All	Yield All	Yield All	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Eme	Yield Eme	Yield Eme	Yield Eme	Yield Eme
CO_2/GDP	2.184					6.567					-5.006				
	(5.958)					(7.139)					(6.426)				
CO_2/GDP x PostParis	1.913					1.071					4.168*				
	(1.696)					(3.124)					(2.205)				
RenewableEnergy		-0.087*					-0.041					-0.115*			
		(0.050)					(0.066)					(0.065)			
RenewableEnergy x PostParis		-0.015					-0.011*					-0.056**			
		(0.009)					(0.007)					(0.024)			
OilGasCoalRents			-1.005*					-0.185					-1.547***		
			(0.519)					(0.725)					(0.576)		
OilGasCoalRents x PostParis			0.228					0.628					0.048		
			(0.418)					(0.479)					(0.552)		
TreatyParticipation				0.262					0.466*					0.507	
				(0.218)					(0.240)					(0.630)	
TreatyParticipation x PostParis				-0.332***					-0.183**					-0.793**	
				(0.098)					(0.080)					(0.402)	
SDIReversed					4.925					3.773					0.240
					(5.051)					(5.761)					(7.482)
SDIReversed x PostParis					0.745					0.929					4.915
					(1.005)					(1.221)					(3.989)
Observations	659	602	602	702	659	374	343	343	405	374	285	259	259	297	285
R-squared within	-0.068	0.108	-0.162	-0.025	-0.360	0.372	0.412	0.331	0.440	0.135	-1.095	0.172	-0.651	-3.898	-1.213
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Transition risk, credit rating regression (with post-Paris dummy)

OLS estimates from Model 5 with country-clustered standard errors and two-way fixed effects. The dependent variable is the credit rating; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Rating All	Rating All	Rating All	Rating All	Rating All	Rating Adv	Rating Adv	Rating Adv	Rating Adv	Rating Adv	Rating Eme	Rating Eme	Rating Eme	Rating Eme	Rating Eme
CO_2/GDP	-2.284					-3.639					2.442				
	(2.928)					(9.323)					(1.637)				
CO_2/GDP x PostParis	-2.831**					1.455					-2.746***				
	(1.148)					(1.435)					(0.988)				
RenewableEnergy		0.003					0.005					-0.067**			
		(0.025)					(0.051)					(0.027)			
RenewableEnergy x PostParis		0.004					0.010					0.003			
		(0.005)					(0.008)					(0.007)			
OilGasCoalRents			0.214					-0.119					0.227		
			(0.168)					(0.412)					(0.186)		
OilGasCoalRents x PostParis			-0.351**					-0.258					-0.248*		
			(0.137)					(0.346)					(0.127)		
TreatyParticipation				-0.307					-0.028					-0.756**	
				(0.235)					(0.192)					(0.354)	
TreatyParticipation x PostParis				0.134					0.135**					0.268	
				(0.119)					(0.067)					(0.225)	
SDIReversed					2.098					2.941					1.614
					(2.229)					(2.611)					(2.157)
SDIReversed x PostParis					-0.343					-1.553**					-2.060*
					(0.628)					(0.771)					(1.248)
Observations	903	829	824	950	903	396	363	363	429	396	507	466	461	521	507
R-squared within	0.157	0.224	0.169	-0.137	0.229	0.171	0.169	0.075	-0.348	-0.112	0.424	0.464	0.443	-1.289	0.426
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

5.2 Physical risk

5.2.1 Temperature change

The *TemperatureChange* variable does not exhibit a pricing effect in any of the country sample groups in the basic yield regression (Model 1, Table 5). However, when looking at the post-Paris specification of the model we observe more nuanced patterns. For advanced countries, temperature exposure is initially insignificant (Model 4, Table 6), but a significant relationship emerges when credit ratings are excluded as a control (Model 6, Appendix 13) — here, in the post-Paris period, a one degree increase in temperature corresponds to an approximate 32 basis points increase in government bond yields. These results suggest that the effect of temperature change on sovereign yields in advanced countries operates through changes in perceived creditworthiness. This is supported by our post-Paris credit rating model (Model 5, Table 7), where the coefficient of the post-Paris interaction term is statistically significant and associated with lower ratings in advanced countries. This interpretation is also consistent with the environmental criteria applied by credit rating agencies (Appendix 1), which explicitly incorporate factors such as long-term shifts in climate patterns. In summary, these results suggest that temperature changes impact the sovereign yields of advanced countries, and that a significant part of this effect operates through credit ratings rather than through direct market pricing.

Cappiello et al. (2025) also show that greater temperature anomalies are associated with lower sovereign credit ratings. Moreover, they find that this effect is primarily driven by EU countries and advanced countries, which closely aligns with our results for the advanced sample as a great portion of our advanced countries are EU countries. On the other hand, Anyfantaki et al. (2025) generally find limited effects of temperature changes on government bond yields over the long term, the exception being for countries with high GDP growth. Our findings complement this by suggesting that temperature-driven yield effects in advanced countries may diminish or disappear once credit ratings are controlled for — pointing to the ratings channel as a key transmission mechanism.

When introducing the post-Paris interaction term (Model 4, Table 6), the standalone coefficient for the emerging/developing subsample becomes statistically significant, while the interaction term does not. Böhm (2022) finds similar results, showing that in emerging and developing countries greater temperature anomalies are associated with reduced sovereign bond performance, but that this relationship has not strengthened significantly following the Paris Agreement. Using Model 7 we test for the non-linear effect found by Böhm (2022), according to which the effect of temperature anomalies on government bond yields is stronger in warmer countries. When setting the Group Dummy, High Temperature, to equal the warmest quarter of countries in our dataset (based on average temperature 1951–1980[1]), and interacting it with the *TemperatureChange* variable, we find a weak — statistically insignificant — indication of Böhm's non-linear effect being present (Appendix 17).

When adding a post-Paris interaction term to our credit ratings model (Model 5, Table 7) we find no statistically significant relationship between the *TemperatureChange* variable and sovereign credit ratings for the emerging/developing subsample. This shows that for emerging and developing countries, the effect of temperature change on sovereign yields is unlikely to be transmitted through the ratings channel.

5.2.2 Climate disaster frequency

Acute physical risk, represented by our variable *DisasterFrequency*, is not statistically significant in the basic yield specification (Model 1, Table 5), although coefficients show the expected positive sign. On the other hand, in the post-Paris specification all post-Paris interaction coefficients become positive and statistically significant, indicating the emergence of a positive

[1] Which means that this country group, unlike the previous ones, does not change between years.

relationship with yields across all samples (Model 4, Table 6). Though the advanced country subsample exhibits a countervailing — yield-decreasing — effect in its standalone coefficient, the total effect is always positive in the post-Paris period, and statistically significant in the case of the full sample. We interpret the significant, positive coefficients of the interaction terms as markets becoming more responsive to realised and observable climate shocks following an increase in climate awareness and policy focus after the Paris Agreement. The post-Paris shift in the pricing of disaster frequency appears economically meaningful; the period is associated with an incremental increase of 6.8–7.5 basis points per additional climate disaster across country samples. In the full sample, the total effect of disaster frequency amounts to 4.3 basis points per additional climate disaster.

These patterns are compatible with the findings of Anyfantaki et al. (2025), where acute climate events can have a significant economic impact in specific settings. In the case of climate disasters, Anyfantaki et al. (2025) find that following the Paris Agreement, their impact on government bond yields is magnified when fiscal vulnerability is present. Our results add a complementary nuance to this: even without conditioning on additional factors, climate disasters become more clearly associated with higher yields after the Paris Agreement, suggesting that markets increasingly treat such events as relevant for government bond pricing.

Post-Paris, the credit ratings of advanced countries become more sensitive to climate disaster frequency, with disasters being associated with lower ratings (Model 5, Table 7). This is consistent with the qualitative criteria used by credit rating agencies, which explicitly reference event-driven physical risks such as hurricanes and other climate-related disasters (Appendix 1). We find no significant effect on the standalone term, suggesting that credit rating agencies primarily began to incorporate acute physical risk in the post-Paris period, for advanced countries. However, the economic magnitude of this change in effect appears limited: each additional recorded climate disaster is associated with a rating decrease of just 0.05 notches on a 1–21 scale, bringing the total effect of a recorded climate disaster to an approximate 0.03-notch decline. This is further supported by the fact that we do not see signs of the pricing of climate disaster frequency in yields being transmitted by credit ratings. Removing ratings as a control does not meaningfully change the results of our post-Paris yield regression (Model 6, Appendix 13).

For emerging and developing countries, no significant effects are observed in the post-Paris specification of the ratings model (Model 5, Table 7). One possible explanation is that when rating agencies assess the creditworthiness of these countries, acute physical risk is pushed to the periphery as other types of risk, such as macroeconomic factors and institutional quality, are deemed more important. Additionally, systematically incorporating disaster-related risks may be particularly challenging for these countries due to data limitations. These results differ from those of Cappiello et al. (2025), who find that acute physical risk is particularly reflected in the credit ratings of emerging countries, as these countries tend to face greater challenges in managing humanitarian crises and rebuilding after natural disasters. One possible explanation for this divergence could be differences in variable construction. While Cappiello et al. (2025) focus on percentage changes in disaster frequency, our measure captures the absolute count of disasters, which may be less sensitive to relative shocks in environments where baseline disaster frequency is low.

Table 5: Physical risk, yield regression (including credit rating as control)

OLS estimates from Model 1 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield Adv	Yield Adv	Yield Eme	Yield Eme
TemperatureChange	0.127 (0.155)		0.102 (0.148)		0.422 (0.371)	
DisasterFrequency		0.008 (0.022)		0.005 (0.024)		0.001 (0.026)
Observations	669	715	392	405	277	310
R-squared within	0.007	-0.011	0.210	0.208	-0.030	-0.082
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Physical risk, yield regression (with credit rating control and post-Paris dummy)

OLS estimates from Model 4 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield Adv	Yield Adv	Yield Eme	Yield Eme
TemperatureChange	0.051 (0.218)		-0.070 (0.230)		0.832** (0.409)	
TemperatureChange x PostParis	0.119 (0.260)		0.309 (0.269)		-0.506 (0.339)	
DisasterFrequency		-0.032 (0.026)		-0.049** (0.025)		-0.032 (0.027)
DisasterFrequency x PostParis		0.075** (0.029)		0.075*** (0.014)		0.068* (0.041)
Observations	669	715	392	405	277	310
R-squared within	-0.041	-0.064	0.087	0.134	0.126	-0.173
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Physical risk, credit rating regression (with post-Paris dummy)

OLS estimates from Model 5 with country-clustered standard errors and two-way fixed effects. The dependent variable is the credit rating; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Rating All	Rating All	Rating Adv	Rating Adv	Rating Eme	Rating Eme
TemperatureChange	0.090 (0.187)		0.401 (0.284)		-0.275 (0.225)	
TemperatureChange x PostParis	0.087 (0.202)		-0.431* (0.258)		0.242 (0.295)	
DisasterFrequency		0.006 (0.021)		0.022 (0.021)		0.003 (0.034)
DisasterFrequency x PostParis		-0.010 (0.018)		-0.049** (0.019)		-0.001 (0.030)
Observations	914	979	416	429	498	550
R-squared within	0.250	0.251	-0.019	0.136	0.435	0.472
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

6. Robustness tests and limitations

As a first robustness test, we rerun the regressions of government bond yields using 5-year maturity yields instead of 10-year maturity yields. The country-time coverage of this alternative dependent variable is very similar to that of our original variable, meaning that the number of observations entering each model is approximately the same. The results of this test are similar to our main results; the general trend is that coefficients keep their signs and magnitudes. There is, however, a trend of lower statistical significance across results. The previously significant coefficients for *CO_2/GDP*, *RenewableEnergy*, and *OilGasCoalRents*, for example, often lose their statistical significance, though their signs and magnitudes are mostly unchanged. We believe that this is due, at least in part, to 5-year maturity yields being 'noisier' than their 10-year counterparts and less inclined to reflect long-term developments and risks. That is, they react more strongly to sudden events and short-term trends vis-à-vis long-term developments. And indeed, the three transition risk variables mentioned capture long-term developments rather than sudden shocks. The coefficients for *TreatyParticipation*, *DisasterFrequency*, and *TemperatureChange* fare a bit better, keeping most of their statistical significance. For the latter two variables, this may be due to them reflecting more immediate fiscal impacts.

We also re-estimate all specifications using the same 10-year government bond yield dependent variable, but winsorised at the 1^{st} and 99^{th} percentiles. The results remain virtually unchanged, indicating that they are not driven by extreme outliers.

Furthermore, we rerun the regressions on *CO_2/GDP*, replacing it with *CO_2/Capita* to test the robustness of results and see if markets and credit rating agencies pay greater, or less, attention to the carbon intensity of a country's consumption, rather than the carbon intensity of its production. Though the coefficients of the alternative variable typically have the same signs and magnitudes as the original one, there is an important difference: the variable presents no statistically significant post-Paris changes in effects, neither with respect to government bond yields nor with respect to credit ratings. Thus, while we find clear indications that credit rating agencies began to increasingly penalise *CO_2/GDP* following the Paris Agreement, the same is not true for *CO_2/Capita*. The weakly significant indication of greater pricing of *CO_2/GDP* in the government bond yields of emerging and developing countries post-Paris, also does not hold for *CO_2/Capita*. We interpret this as market participants attaching greater importance to *CO_2/GDP*, rather than our initial result being a statistical fluke.

We recognise that parts of our analysis may suffer from omitted variable bias. In particular, the weakly significant negative relationship between renewable energy consumption and credit ratings in the emerging/developing subsample may reflect country-specific developments coinciding with changes in renewable energy consumption that are not fully captured by our control variables, rather than a genuine causal relationship.

Climate risk is inherently difficult to measure, and some of our variables are likely imperfect proxies for the underlying risks they are intended to capture. There are several issues with the reversed SDI, for example. The index combines many sub-indicators, the weighting of which may be arbitrary. More important, perhaps, is the fact that approximately half of the measure represents a country's development level rather than climate transition risk.

The variable *TreatyParticipation* assumes that a country's signing of an international climate treaty or convention is a credible signal of future adherence to that treaty or convention. That may not always be the case. Furthermore, climate treaties and conventions may differ vastly; their scope, contents, and implications for signatories may be very different. Additionally, *TemperatureChange* ignores regional temperature variations which may be important, especially in large countries with uneven distribution of economic activity, such as China. And like our transition risk variables, its historical data points may not accurately reflect future temperature projections. *DisasterFrequency*, lastly, suffers from several imperfections. To begin with, it makes no distinction between disasters. If registered, a relatively small flood is given the same weight as one of biblical proportions. In fact, the EM-DAT does state the value of damages and the number of people affected for some disasters, but not often enough for us to be able to use that data in our analysis. Moreover, disaster reporting may be better in some countries than in others.

7. Discussion

7.1 Sustainable finance

Despite broad agreement among policymakers on the need for a sustainable transition, if and to what extent climate risks are reflected in government bond yields remains a rather open question.

The most recent evidence offers a nuanced picture. Anyfantaki et al. (2025) find strong evidence of transition risk being priced into sovereign yields, particularly for emerging countries and increasingly so after the Paris Agreement. On the other hand, they find little indication that physical climate risk is systematically reflected in yields. S&P Global (2025) find a 'greenium' in European corporate bond yields over 2016–2022, only for it to vanish when increasing the number of countries studied and extending the time window to 2024 — an indication that risk premiums can be highly sensitive to the time period and geography studied.

It is perhaps not so surprising, then, that our results only confirm parts of what has been found in previous studies, and that many effects change significantly between time periods. For instance, while several earlier studies found carbon intensity to have a significant impact on government bond yields, we find only limited evidence of this in our more recent sample. The Paris Agreement appears to have been a turning point, after which climate risks became more relevant both for yield pricing and sovereign credit assessments. Whether we have passed another such inflection point is difficult to say, but it is interesting to note that we find a weaker relationship between carbon intensity and sovereign yields than most previous studies in the field.

The stakes here extend well beyond financial markets. How sovereign bond markets price climate risk matters for real economic outcomes; it shapes investment decisions, forms the basis for asset valuations, and ultimately affects a government's ability to fund climate transition, adaptation, infrastructure, and public services. As Kling et al. (2025) argue, when climate risk feeds into governments' borrowing costs, a damaging feedback loop can emerge: higher borrowing costs constrain adaptation investment, which deepens vulnerability, further increasing sovereign risk. Our results show that several types of climate risk are priced in the government bond yields of emerging and developing countries, where vulnerability is the greatest, indicating that this dynamic is present to some extent. This underlines the need for continued research on the role of climate risk in sovereign bond markets. A better understanding of these mechanisms is not only academically valuable, but essential for policymakers, investors, and governments that must ensure a successful climate transition while managing increasing physical climate risks.

7.2 Renewable energy

We find a meaningful negative relationship between renewable energy consumption and sovereign bond yields, across the full sample and particularly among emerging and developing countries. On the other hand, we find little indication of renewable energy consumption being reflected in credit ratings, indicating that the transition risk associated with reliance on unsustainable energy sources is perceived and priced by markets directly, rather than mediated by credit ratings.

Global renewable energy investment reached USD 807 billion in 2024, up 22 percent from the 2022/2023 annual average, reflecting a sustained acceleration in capital flows toward cleaner energy sources (IRENA, 2025). This shift in capital allocation is connected to a broader repricing of energy transition risk. Our results suggest that markets distinguish between countries based on how far along they are in their energy transition, with countries that consume more renewable energy appearing to enjoy somewhat lower borrowing costs. If this relationship is genuine and persistent, it means that the fiscal case for investing in renewable energy is strong as lower sovereign borrowing costs can offset a meaningful share of the upfront investment. That said, further research is needed to establish the strength and direction of this relationship with greater confidence.

Renewable energy may also increasingly function as a hedge against energy supply disruptions. The commodity price shocks of the past decade, in particular the repricing of European energy markets following Russia's invasion of Ukraine in 2022, illustrated the fiscal and macroeconomic vulnerability that comes with a dependence on imported fossil fuels. More recently, shipping disruptions in the Hormuz Strait linked to escalating tensions in the Middle East have again demonstrated how quickly geopolitical events can translate into energy price spikes and broader macroeconomic stress. Countries heavily reliant on energy imports faced surging energy bills, inflationary pressure, and deteriorating current account balances in both episodes, all of which can feed into sovereign risk. Countries that consume a greater share of renewable energy are usually less exposed to these dynamics since their renewable energy is domestically produced, shielding them from the volatility of fossil fuel markets and the stress that follows when supply is disrupted. Our results are consistent with markets recognising this to some degree — countries with greater renewable energy consumption appear to face lower borrowing costs. Future studies with more recent data will be better placed to investigate the presence and magnitude of this effect.

7.3 Credit rating agencies

A broader theme running through our results is the role of credit rating agencies in linking climate risks to financial markets. We find that rating agencies increasingly began to account for certain climate transition risks following the Paris Agreement, such as carbon intensity and oil, gas, and coal rents — notably, this was not the case for renewable energy consumption.

When it comes to physical climate risk, our results for temperature change are particularly interesting: for advanced countries, the effect of temperature change on yields disappears when credit ratings are controlled for, but reappears when they are removed. This shows that credit rating agencies can be active intermediaries through which climate risk is transmitted to sovereign borrowing costs.

These findings speak to the broader role of credit rating agencies in financial markets. Their assessments can influence governments' borrowing costs, shape what institutional investors hold, and affect access to international capital markets — dynamics that may be especially consequential for emerging and developing countries. To the extent that rating agencies do not merely reflect financial reality but also help shape it, how they incorporate climate risks in their assessments may matter beyond the financial sphere. A rating agency that consistently underweights carbon transition risk could, for instance, unintentionally reduce the financial pressure on high-emitting countries to decarbonise.

8. Conclusion

This thesis sets out to examine the relationship between climate risks and two closely related dimensions of sovereign finance: government bond yields and sovereign credit ratings. Contributing to a small but growing literature on the climate-economy nexus in financial markets, we study these two dimensions simultaneously and explicitly model the potential transmission of climate risk pricing from credit ratings to sovereign yields, an aspect that has received limited attention in prior studies. Using a panel dataset of 80 advanced and emerging/developing countries over the period 2010–2023, and treating the Paris Agreement as an exogenous structural event, we investigate how both physical and transition climate risks are reflected in sovereign bond markets and in the assessments of the major credit rating agencies.

Our results paint a nuanced picture. Climate risks are increasingly reflected in sovereign finance, but the extent, channels, and timing of incorporation vary considerably across risk types, country groups, and time periods. The Paris Agreement emerges as an important turning point, after which both markets and credit rating agencies appear to have reassessed the role of climate factors in sovereign risk. Among transition risks, variables related to a country's energy mix and institutional commitment to the green transition show the most consistent direct pricing in government bond yields, while carbon intensity and fossil fuel income dependency exhibit little direct borrowing cost penalty — rating agencies, on the other hand, associate these with lower sovereign ratings in the post-Paris period, hinting at a potential indirect pricing in yields. Also for physical climate risks the story is mixed: direct pricing in government bond yields remains limited, though indirect transmission through credit ratings emerges for certain risk types and country groups, and climate disaster frequency shows signs of more direct incorporation following the Paris Agreement.

A broader theme running through our findings is the role of credit rating agencies as intermediaries in this process. Since their sovereign ratings do not merely reflect financial reality, but also shape it, their incorporation of climate risks has implications that go beyond the financial sphere. Our results suggest that this incorporation, while growing in the post-Paris period, remains uneven across risk types. If sovereign ratings and government bond yields come to reflect climate risk more fully, they may in turn influence the very investments in mitigation, adaptation and transition that determine future vulnerability — a dynamic that could be especially consequential for emerging and developing countries, where exposure is greatest and fiscal room the most constrained.

How sovereign bond markets price climate risk is not merely an academic question. It shapes investment decisions, affects governments' room to manoeuvre, and ultimately influences whether the international financial system supports or hinders the climate transition. Our findings show that this relationship is complex and varies across risk types, country groups, and transmission channels, underscoring the need for careful empirical analysis. Continued research in this area, extending the time horizon, refining the measurement of climate risks and opportunities, and further unpacking the relationship between ratings and yields, will be essential as both climate change and financial markets continue to develop.

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Appendix

Appendix 1: Environmental factors considered for sovereign ratings from S&P, Moody's & Fitch

	S&P	Moody's	Fitch
Environmental Credit Factors	▪ Climate transition risk factors, including those related to climate policy; legal, technology, and market changes to address mitigation; and adaptation requirements related to climate change; ▪ Physical risk factors, including event-driven or longer-term shifts in climate patterns, such as hurricanes or chronic heat waves; ▪ Natural capital factors, related to the stock of natural resources, which include plants, animals, soils, minerals, and air; ▪ Waste and pollution factors, such as waste products, water pollutants, and air emissions other than greenhouse gas emissions; and ▪ Other environmental factors	▪ Carbon transition ▪ Physical climate risks ▪ Water management ▪ Waste and pollution ▪ Natural capital	▪ GHG Emissions and Air Quality ▪ Energy Management ▪ Water Resources and Management ▪ Biodiversity and Natural Resources ▪ Natural Disasters and Climate Change

Appendix 2: Countries included in the analysis, divided into advanced and emerging/developing subsamples

Advanced Countries	Emerging/Developing Countries
Australia	Argentina
Austria	Bahrain
Belgium	Bangladesh
Canada	Botswana
Croatia	Brazil
Cyprus	Bulgaria
Czech Republic	Burkina Faso
Denmark	Chile
Finland	China
France	Colombia
Germany	Egypt
Greece	Georgia
Hong Kong	Ghana
Iceland	Hungary
Ireland	India
Israel	Indonesia
Italy	Ivory Coast
Japan	Jordan
Latvia	Kazakhstan
Lithuania	Kenya
Malta	Malaysia
Netherlands	Mauritius
New Zealand	Mexico
Norway	Morocco
Portugal	Namibia
Singapore	Nigeria
Slovakia	Pakistan
Slovenia	Peru
South Korea	Philippines
Spain	Poland
Sweden	Qatar
Switzerland	Romania
Taiwan	Russia
UK	Saudi Arabia
US	Senegal
	Serbia
	South Africa
	Sri Lanka
	Tanzania
	Thailand
	Togo
	Turkey
	Uganda
	Venezuela
	Vietnam

Appendix 3: List of variables, including descriptions, data sources, transformations, and coverage periods

Variable	Description	Source	Transformation	Coverage
10y yield	10-year government benchmark yields, collected at monthly frequency and averaged to annual observations	LSEG Workspace		2010–2023
5y yield	5-year government benchmark yields, collected at monthly frequency and averaged to annual observations	LSEG Workspace		2010–2023
CreditRating	Numeric variable based on average long-term issuer ratings from S&P, Moody's, and Fitch, converted using the same scale as Cappiello et al. (2025)	LSEG Workspace		2010–2023
CO_2/GDP	Metric tonnes of carbon emissions relative to GDP	Our World in Data		2010–2022
CO_2/Capita	Metric tonnes of carbon emission equivalent per capita	World Bank	Log transformation to handle right-skewness	2010–2023
RenewableEnergy	Renewable energy consumption as a percentage of total final energy consumption	World Bank		2010–2021
OilGasCoalRents	Oil, natural gas, and coal rents as a percentage of GDP	World Bank	Square root transformation to handle right-skewness and concentration of values near zero	2010–2021
TreatyParticipation	Number of environmental treaties and conventions signed by a given year	United Nations Statistics Department		2010–2023
SDIReversed	Reversed Sustainable Development Index, calculated as −1 × (Human Development Index / Ecological Impact Index). The HDI reflects life expectancy, education, and income. The Ecological Impact Index reflects the extent to which consumption-based CO_2 emissions and material footprint exceed per-capita shares of planetary boundaries	Hickel (2020)		2010–2022
TemperatureChange	Difference between a country's annual average temperature and its average temperature over the baseline period 1951–1980	World Bank		2010–2023
DisasterFrequency	Total number of climate-related natural disasters recorded in a given year, including floods, storms, extreme temperatures, wildfires, droughts, and landslides. Multi-year disasters are assigned to their first year	EM-DAT via the IMF		2010–2023
GrossGovernmentDebt /GDP	Gross government debt as a percentage of GDP	IMF		2010–2023

CyclicallyAdjPrimary Balance/GDP	Cyclically adjusted government primary surplus as a percentage of GDP	IMF		2010–2023
Inflation	Annual change in the consumer price index	World Bank	Winsorised, 1% level	2010–2023
GDPgrowth	Real GDP growth rate in constant national currency	World Bank		2010–2023
CurrentAccount/GDP	Current account balance as a percentage of GDP	World Bank		2010–2023
GovernmentEffectiveness	Composite indicator capturing the quality of public services, civil service independence, policy formulation and implementation, and government credibility. Expressed in units of a standard normal distribution, ranging from approximately −2.5 to 2.5	World Bank		2010–2023
LogTradeOpenness/GDP	Total trade (exports plus imports) as a percentage of GDP	World Bank	Log transformation to handle right-skewness	2010–2023
LogExchangeRate	Annual average exchange rate of the local currency against the US dollar	Bank for International Settlements (BIS)	Log transformation to handle right-skewness	2010–2023
LogGDP/Capita	GDP per capita in current US dollars	World Bank	Log transformation to handle right-skewness	2010–2023
DebtInDefaultDummy	Dummy variable taking the value 1 if a country has any government debt in default in a given year, and 0 otherwise	BoC-BoE Sovereign Default Database		2010–2023
PostParis (Dummy)	Dummy variable taking the value 1 from 2016 onwards and 0 in prior years			

Appendix 4: Converting scale for the long-term issuer ratings of: Standard & Poor (S&P), Moody's, and Fitch

Rating Agency			**Numerical Rating**	**Rating grade**	
S&P	**Moody's**	**Fitch**			
AAA	Aaa	AAA	21	Prime high grade	Investment grade
AA+	Aa1	AA+	20		
AA	Aa2	AA	19	High grade	
AA-	Aa3	AA-	18		
A+	A1	A+	17		
A	A2	A	16	Upper medium grade	
A-	A3	A-	15		
BBB+	Baa1	BBB+	14		
BBB	Baa2	BBB	13	Lower medium grade	
BBB-	Baa3	BBB-	12		
BB+	Ba1	BB+	11		Non-investment grade
BB	Ba2	BB	10	Speculative	
BB-	Ba3	BB-	9		
B+	B1	B+	8		
B	B2	B	7	Highly speculative	
B-	B3	B-	6		
CCC+	Caa1	CCC+	5		
CCC	Caa2	CCC	4	Substantial risks	
CCC-	Caa3	CCC-	3		
CC			2		
C		CC	2	Extremely speculative	
CI	Ca	C	2		
R			1		
SD			1	In default	
D	C	D	1		
NR		NR	-	No rating	

Appendix 5: Control variables summary statistics

	N	Mean	Min	Max	Std	Within Std
All countries						
GrossGovernmentDebt/GDP	1106	61.81	0.05	336.54	39.84	14.99
CyclicallyAdjPrimaryBalance/GDP	849	-1.08	-12.14	14.40	2.99	2.41
Inflation	1077	4.39	-1.32	40.97	5.90	3.53
GDPgrowth	1092	3.04	-30.00	24.62	4.05	3.51
CurrentAccount/GDP	1095	-0.16	-20.56	33.18	5.97	3.44
GovernmentEffectiveness	1092	0.52	-1.89	2.32	0.87	0.15
LogTradeOpenness/GDP	1085	4.35	3.11	6.09	0.58	0.12
LogExchangeRate	1114	2.46	-0.98	10.08	2.70	0.26
LogGDP/Capita	1106	9.41	6.44	11.60	1.31	0.17
DebtInDefaultDummy	1120	0.29	0.00	1.00	0.46	0.22
Advanced						
GrossGovernmentDebt/GDP	476	77.33	0.05	258.37	46.10	11.38
CyclicallyAdjPrimaryBalance/GDP	462	-1.02	-12.14	14.40	3.24	2.46
Inflation	462	2.24	-1.32	19.71	2.61	2.49
GDPgrowth	462	2.21	-10.94	24.62	3.50	3.19
CurrentAccount/GDP	476	1.92	-20.56	28.63	5.71	3.06
GovernmentEffectiveness	462	1.33	0.12	2.32	0.48	0.13
LogTradeOpenness/GDP	476	4.58	3.15	6.09	0.60	0.09
LogExchangeRate	490	0.85	-0.50	7.18	1.77	0.10
LogGDP/Capita	476	10.57	9.32	11.60	0.49	0.13
DebtInDefaultDummy	490	0.04	0.00	1.00	0.20	0.12
Emerging/Developing						
GrossGovernmentDebt/GDP	630	50.08	1.50	336.54	29.39	17.24
CyclicallyAdjPrimaryBalance/GDP	387	-1.14	-10.96	9.42	2.65	2.36
Inflation	615	6.00	-1.32	40.97	7.06	4.14
GDPgrowth	630	3.65	-30.00	19.59	4.32	3.72
CurrentAccount/GDP	619	-1.75	-19.95	33.18	5.67	3.71
GovernmentEffectiveness	630	-0.07	-1.89	1.20	0.56	0.17
LogTradeOpenness/GDP	609	4.17	3.11	5.23	0.50	0.13
LogExchangeRate	624	3.71	-0.98	10.08	2.64	0.34
LogGDP/Capita	630	8.54	6.44	11.59	1.04	0.20
DebtInDefaultDummy	630	0.49	0.00	1.00	0.50	0.27

Appendix 6: Yield baseline regression

OLS estimates from Model 1 with country-clustered standard errors and two-way fixed effects, estimated as a baseline, without climate variables. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All Countries
GDPgrowth (t-1)	-0.104** (0.043)
Inflation (t-1)	0.105** (0.049)
GrossGovernmentDebt/GDP (t-1)	-0.030 (0.023)
CyclicallyAdjPrimaryBalance/GDP (t-1)	-0.062 (0.048)
CurrentAccount/GDP (t-1)	-0.031 (0.034)
LogTradeOpenness/GDP (t-1)	-4.261** (1.726)
LogExchangeRate (t-1)	3.513*** (0.795)
GovernmentEffectiveness (t-1)	-0.702 (0.627)
CreditRating (t-1)	-0.331* (0.190)
No. Observations	715
R-squared	0.313
R-squared within	-0.011
Entity FE	Yes
Time FE	Yes

Appendix 7: Rating baseline regression

OLS estimates from Model 2 with country-clustered standard errors and two-way fixed effects, estimated as a baseline, without climate variables. The dependent variable is the credit rating; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Rating All Countries
LogGDP/Capita (t-1)	0.958 (0.681)
GDPgrowth (t-1)	0.107*** (0.037)
Inflation (t-1)	-0.017 (0.025)
GrossGovernmentDebt/GDP (t-1)	-0.038*** (0.008)
CurrentAccount/GDP (t-1)	-0.021 (0.014)
GovernmentEffectiveness (t-1)	0.967* (0.560)
DebtInDefaultDummy (t-1)	-0.139 (0.163)
No. Observations	979
R-squared	0.344
R-squared within	0.251
Entity FE	Yes
Time FE	Yes

Appendix 8: Transition risk, credit rating regression

OLS estimates from Model 2 with country-clustered standard errors and two-way fixed effects. The dependent variable is the credit rating; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Rating All	Rating All	Rating All	Rating All	Rating All	Rating Adv	Rating Adv	Rating Adv	Rating Adv	Rating Adv	Rating Eme	Rating Eme	Rating Eme	Rating Eme	Rating Eme
CO_2/GDP	-1.279					-4.232					3.732*				
	(2.942)					(9.537)					(1.991)				
RenewableEnergy		0.001					0.018					-0.071***			
		(0.025)					(0.048)					(0.026)			
OilGasCoalRents			0.414**					-0.160					0.359*		
			(0.191)					(0.420)					(0.215)		
TreatyParticipation				-0.250					0.025					-0.587**	
				(0.219)					(0.180)					(0.274)	
SDIReversed					1.742					1.245					0.408
					(2.132)					(2.668)					(2.271)
Observations	903	829	824	950	903	396	363	363	429	396	507	466	461	521	507
R-squared within	0.229	0.217	0.204	0.223	0.239	0.176	0.131	0.107	0.149	0.165	0.469	0.473	0.459	0.481	0.456
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 9: Transition risk, yield regression (excluding credit rating control)

OLS estimates from Model 3 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield All	Yield All	Yield All	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Eme	Yield Eme	Yield Eme	Yield Eme	Yield Eme
CO_2/GDP	-0.118					11.510					-5.678				
	(6.586)					(11.975)					(6.058)				
RenewableEnergy		-0.070*					-0.051					-0.098			
		(0.041)					(0.072)					(0.073)			
OilGasCoalRents			-0.939*					-0.030					-1.548***		
			(0.565)					(0.825)					(0.591)		
TreatyParticipation				0.181					0.514*					-0.314	
				(0.228)					(0.279)					(0.552)	
SDIReversed					5.801					3.200					4.256
					(5.038)					(4.901)					(5.623)
Observations	659	602	602	702	659	374	343	343	405	374	285	259	259	297	285
R-squared within	-0.217	-0.101	-0.285	-0.159	-0.330	0.348	0.222	0.165	-0.116	0.119	-0.409	-0.267	-0.681	0.011	-0.376
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 10: Transition risk, yield regression (excluding credit rating control, with post-Paris dummy)

OLS estimates from Model 6 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield All	Yield All	Yield All	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Adv	Yield Eme	Yield Eme	Yield Eme	Yield Eme	Yield Eme
CO_2/GDP	1.784					11.081					-3.150				
	(6.193)					(10.920)					(6.281)				
CO_2/GDP x PostParis	2.427					-0.986					2.562				
	(1.550)					(3.798)					(1.929)				
RenewableEnergy		-0.054					-0.035					-0.101			
		(0.042)					(0.071)					(0.067)			
RenewableEnergy x PostParis		-0.017*					-0.012					-0.058**			
		(0.009)					(0.008)					(0.024)			
OilGasCoalRents			-0.902*					-0.040					-1.537***		
			(0.524)					(0.797)					(0.581)		
OilGasCoalRents x PostParis			0.222					0.574					0.057		
			(0.410)					(0.426)					(0.552)		
TreatyParticipation				0.329					0.550**					0.492	
				(0.205)					(0.269)					(0.634)	
TreatyParticipation x PostParis				-0.323***					-0.180**					-0.799**	
				(0.103)					(0.086)					(0.394)	
SDIReversed					4.718					1.721					1.116
					(5.218)					(5.597)					(8.122)
SDIReversed x PostParis					1.001					1.416					3.031
					(0.920)					(1.169)					(4.394)
Observations	659	602	602	702	659	374	343	343	405	374	285	259	259	297	285
R-squared within	-0.351	0.028	-0.301	0.048	-0.537	0.378	0.261	0.176	0.340	-0.114	-0.614	0.136	-0.693	-4.045	-0.732
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 11: Physical risk, credit rating regression

OLS estimates from Model 2 with country-clustered standard errors and two-way fixed effects. The dependent variable is the credit rating; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Rating All	Rating All	Rating Adv	Rating Adv	Rating Eme	Rating Eme
TemperatureChange	0.149		0.153		-0.079	
	(0.115)		(0.167)		(0.130)	
DisasterFrequency		-0.000		-0.014		0.002
		(0.015)		(0.024)		(0.022)
Observations	914	979	416	429	498	550
R-squared within	0.249	0.251	0.154	0.141	0.481	0.472
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 12: Physical risk, yield regression (excluding credit rating control)

OLS estimates from Model 3 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield Adv	Yield Adv	Yield Eme	Yield Eme
TemperatureChange	0.115 (0.152)		0.061 (0.133)		0.411 (0.350)	
DisasterFrequency		0.006 (0.017)		0.015 (0.036)		0.002 (0.027)
Observations	669	715	392	405	277	310
R-squared within	-0.099	-0.102	0.055	0.052	-0.014	-0.060
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 13: Physical risk, yield regression (excluding credit rating control, with post-Paris dummy)

OLS estimates from Model 6 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. All, Adv, and Eme denote the full sample, advanced, and emerging/developing. The sample covers 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All	Yield All	Yield Adv	Yield Adv	Yield Eme	Yield Eme
TemperatureChange	-0.048 (0.249)		-0.263 (0.222)		0.833** (0.409)	
TemperatureChange x PostParis	0.258 (0.298)		0.585* (0.312)		-0.514 (0.329)	
DisasterFrequency		-0.031* (0.019)		-0.038 (0.035)		-0.032 (0.027)
DisasterFrequency x PostParis		0.070*** (0.026)		0.075*** (0.021)		0.069* (0.041)
Observations	669	715	392	405	277	310
R-squared within	-0.215	-0.162	-0.215	-0.032	0.134	-0.156
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 14: CO_2/GDP, credit ratings regression (triple interaction)

OLS estimates from Model 9 with country-clustered standard errors and two-way fixed effects. The dependent variable is the credit rating; variable definitions are in Appendix 3. The sample covers the full country sample, 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Credit Rating All countries
CO_2/GDP	-1.699 (2.774)
CO_2/GDP x PostParis	-0.732 (2.181)
CO_2/GDP x High Emitter	-0.888 (2.932)
CO_2/GDP x PostParis x High Emitter	-1.619 (1.366)
Observations	903
R-squared within	0.244
Entity FE	Yes
Time FE	Yes

Appendix 15: RenewableEnergy, yield regression (double interaction)

OLS estimates from Model 7 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. The sample covers the full country sample, 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All Countries
RenewableEnergy	-0.096* (0.049)
RenewableEnergy x Low Renewables	0.091** (0.036)
Observations	602
R-squared within	0.078
Entity FE	Yes
Time FE	Yes

Appendix 16: TreatyParticipation, yield regression (triple interaction)

OLS estimates from Model 8 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. The sample covers the full country sample, 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All Countries
TreatyParticipation	0.231 (0.216)
TreatyParticipation x PostParis	-0.339*** (0.105)
TreatyParticipation x High Emitter	0.106 (0.073)
TreatyParticipation x PostParis x High Emitter	0.002 (0.047)
Observations	702
R-squared within	-0.079
Entity FE	Yes
Time FE	Yes

Appendix 17: TemperatureChange, yield regression (double interaction)

OLS estimates from Model 7 with country-clustered standard errors and two-way fixed effects. The dependent variable is the 10-year yield; variable definitions are in Appendix 3. The sample covers the full country sample, 2010–2023. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	Yield All Countries
TemperatureChange	0.104 (0.159)
TemperatureChange x HighTemperature	1.073 (0.720)
Observations	669
R-squared within	0.009
Entity FE	Yes
Time FE	Yes

Appendix 18: Data Collection note

The analysis in this thesis is conducted using a dataset created by the authors. To create the dataset, the following steps were followed:

I. Raw data for each variable is downloaded from the data sources stated in Appendix 3
II. All raw data is gone through and cleaned
III. A long panel format is applied to all cleaned data
IV. All cleaned data is merged in a single file to create the complete dataset

Appendix 19: AI-disclosure

Tools Used and How	i) Claude was used selectively during the thesis writing process to refine language and improve the formulation of arguments, including rewriting unclear sentences, improving flow, and suggesting alternative phrasings. All analytical reasoning, interpretations, and arguments are entirely our own. ii) Gemini was used as a support tool when developing our code.
Contributions to Thesis Quality	i) The use of generative AI has helped improve the clarity and readability of the written text, allowing our arguments to be communicated more precisely. ii) Using Gemini increased our efficiency in coding and debugging, in turn enabling a more robust and reliable empirical analysis.
Potential Risks and Mitigating Measures	i) A potential risk when using generative AI for writing support is that one becomes overly reliant on it, accepting suggested phrasings uncritically even when they are imprecise, unclear, or do not accurately reflect the intended argument. To mitigate this, we used AI tools selectively rather than routinely, and carefully reviewed all suggested phrasings before incorporating them, editing or discarding proposals that did not precisely capture our own reasoning. ii) A similar risk applies to the use of generative AI in coding. Relying on AI-generated code without fully understanding it makes it difficult to identify potential errors or misspecifications. As with writing, we therefore used AI tools selectively, manually verified all code, and cross-checked all results to ensure their validity.
Insights Gained	i) On the whole, using generative AI as a writing aid has given us a better sense of how to communicate complex ideas clearly and concisely in academic writing. ii) Similarly, using generative AI as a coding aid has sharpened our problem-solving skills and broadened our understanding of alternative implementation approaches.