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Creditworthy: do climate change risks matter for sovereign credit ratings?

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Abstract

Do sovereign credit ratings take into account physical and transition climate risks? This paper empirically addresses this question using a panel dataset that includes a large sample of countries over two decades. The analysis reveals that higher temperature anomalies and more frequent natural disasters—key indicators of physical risk—are associated with lower credit ratings. In contrast, transition risk factors do not appear to be systematically integrated into credit ratings throughout the entire sample period. However, following the Paris Agreement, countries with greater exposure to natural disasters received comparatively lower ratings, suggesting that credit rating agencies are increasingly recognizing the significance of physical risk for sovereign balance sheets. Additionally, more ambitious CO2 emission reduction targets and actual reductions in CO2 emission intensities are associated with higher ratings post-Paris Agreement, indicating that credit rating agencies are beginning to pay more attention to transition risk. At the same time, countries with high levels of debt and those heavily reliant on fossil fuel revenues tend to receive lower ratings after the Paris Agreement. Conversely, sovereigns that stand to gain from the green transition—through revenues from transition-critical materials—are assigned higher sovereign ratings after 2015.

Keywords: Credit ratings; Climate change; Sovereign bonds; Physical risk; Transition risk
JEL Classification: G15, G24, F3, F64, H64

Non-technical summary

The economic consequences of climate change are the focus of thriving research and policy discussions. It is generally anticipated that climate change will exert pressure on the fiscal positions of countries due to rising costs associated with more frequent and severe extreme weather events, needed investments in adaptation, and financing for the transition to a sustainable economy. The creditworthiness of a sovereign, as measured by sovereign ratings assigned by credit rating agencies, should reflect these pressures.

However, despite claims that credit rating agencies are increasingly paying attention to climate-related risks in their assessments, it remains unclear whether they are doing so systematically. Data limitations, uncertainties regarding the accurate measurement of the economic impact of climate change, and doubts about governments' ability to effectively pursue their net-zero commitments, coupled with a rating architecture that is too short-term, are often cited as factors hindering a more systematic integration of climate risks into sovereign ratings. Understanding the extent to which sovereign ratings incorporate climate risks is crucial, as these ratings play a significant role in guiding investment decisions and are embedded in the policies of governments, regulators, and central banks.

In this context, this study addresses the following questions: Do credit rating agencies systematically incorporate climate risks into sovereign credit rating assessments? To what extent are different types of climate risks—notably, physical and transition risks—integrated into their models? Have credit rating agencies assigned higher weight to climate-related factors in their sovereign rating assessments following the Paris Agreement in 2015? This study examines these questions by analysing data from a large sample of countries, including both advanced and emerging economies.

Based on two decades of data for a sample of 124 countries, the study finds that higher temperature anomalies and more frequent natural disasters—measures of physical risk—are associated with lower ratings when controlling for a standard set of rating determinants. In contrast, measures of transition risk linked to the uncertainty of the green transition, such as the energy and emission intensity of an economy and the ambition of its decarbonisation efforts, are not systematically considered in credit ratings.

The study also shows that after the Paris agreement, countries with greater exposure to physical risk received lower ratings, reflecting the expectation that natural disasters would significantly impact sovereign balance sheets, as well as a shift in the attitudes of credit rating agencies, which have begun to pay closer attention to physical risks. In terms of transition policies, reductions in CO2 emission intensities are also associated with higher ratings after the Paris Agreement, suggesting that credit rating agencies have begun to acknowledge transition risks in their assessments of creditworthiness since 2015.

Focusing on subsamples of countries particularly exposed to the green transition, the study finds that countries with a high level of debt and those more reliant on revenues from fossil fuels have received lower ratings after the Paris Agreement. Conversely, countries that stand to gain from the green transition, due to their revenues from transition-critical materials, are assigned higher sovereign ratings since 2015.

1 Introduction

The macroeconomic and financial repercussions of climate change are a major focus of research in economics. Climate change is recognised as a significant risks to sovereign debt sustainability due to the fiscal costs of natural disasters, the need for adaptation investments, and financing for the green transition (Mallucci, 2022; Klusak et al., 2023; Volz et al., 2020; Zenios, 2022).

Climate risk can affect a country's creditworthiness through climate events (*physical risk*) and the transition to net zero (*transition risk*). Extreme climate events (*acute* physical risk) and long-term climate shifts (*chronic* physical risk) can damage public assets and harm the overall economy, leading to reduced tax revenues (see Figure 1). In low-income countries, climate disasters may lead to humanitarian crises, necessitating public intervention. Furthermore, recent international treaties and heightened public awareness of climate change may foster actions focused on adaptation (e.g., infrastructure to address physical risk) and mitigation (e.g., greening the production system).

Unexpected physical damages, humanitarian crises, adaptation measures, and policies aimed at reducing carbon emissions are likely to increase public expenditures and eventually worsen public debt sustainability (United Nations, 2018). Additionally, foregone earnings due to physical damages to industrial assets and the shift towards a greener economy can significantly impact sovereign financial positions. In this context, credit rating agencies (CRAs) assessing the risks to sovereign debt sustainability should systematically heed climate risks in their rating assessments (Standard & Poor's, 2021).

Despite claims that CRAs are increasingly paying attention to climate-related risks in their rating assessments, it remains unclear whether they are doing so systematically. The extent to which various types of climate change-related risks—acute and chronic physical risks, as well as transition risks—are included in these assessments is also uncertain.[1] These are relevant questions, as credit ratings play a crucial role in steering investment decisions and are embedded in the policies of governments, regulators, and central banks.[2]

[1] Data limitations, uncertainties associated with accurately measuring the economic impact of climate change, uncertainties over the ability of governments to effectively pursue their net-zero commitments, and a rating architecture that is too short-term are typically mentioned as factors hindering a more systematic account of climate risks in sovereign ratings (see, e.g., NGFS, 2022 and Klusak et al., 2023).

[2] For example, following its 2021 Strategy Review, the ECB stated that it would explore to what extent climate risk is included in credit ratings (European Central Bank, 2021). Similarly, the Bank of England recently

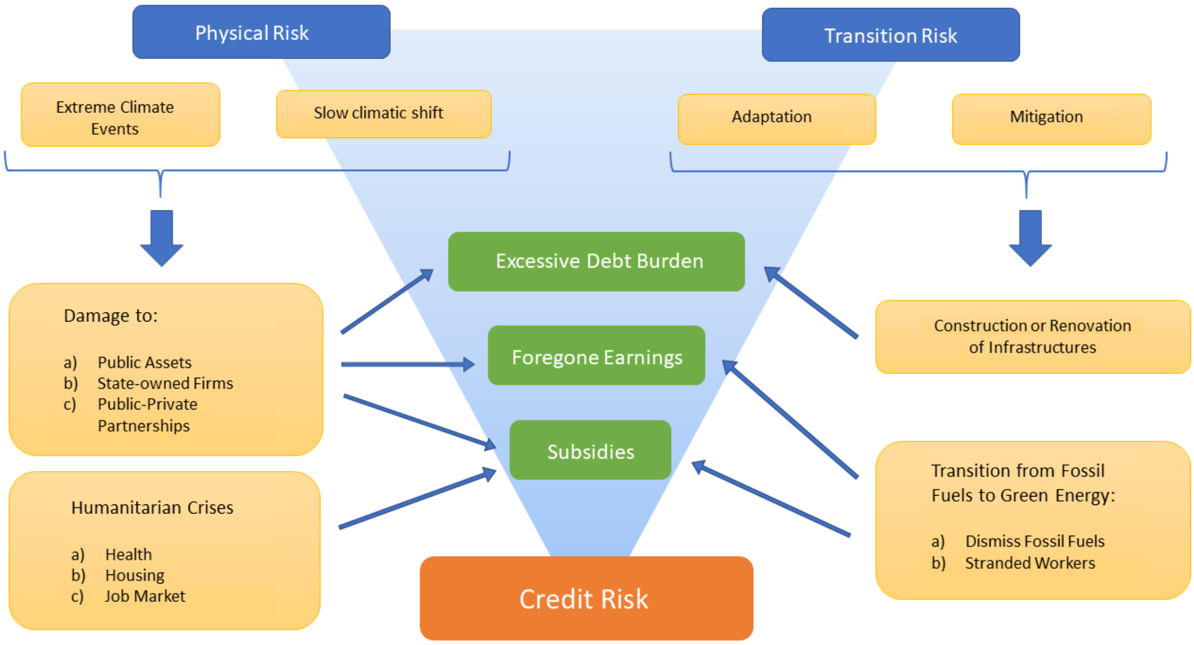

Figure 1: Transmission channels from climate (physical and transition) risks to sovereign credit risk. Physical and transition risks can result in foregone earnings and necessitate subsidies for the private sector, along with aid for communities, leading to excessive debt burdens. These factors can weaken the financial position of sovereigns and diminish their creditworthiness.

Against this backdrop, this study addresses the following questions: Do CRAs systematically incorporate climate physical and transition risks into their sovereign credit rating assessments? To what extent are different types of risks included in their models? Have CRAs assigned greater weight to climate-related factors in their sovereign rating assessments following the Paris Agreement in 2015?

Based on a large sample of sovereign credit ratings including both advanced and emerging economies, we find that higher temperature anomalies and an increased occurrence of natural disasters are associated with lower ratings. Thus, exposure to physical risks, which varies across countries, is considered when evaluating the probability of default for sovereigns. Consistently, when indicators of countries' *readiness* to face the effects of climate change are included, countries with higher scores tend to have, on average, higher ratings. However, despite their statistical significance, physical risk variables play only a marginal role in determining credit ratings in terms of economic impact.

encouraged research in this area (Bank of England, 2023).

Transition risks are particularly challenging to assess for sovereigns. In this study, we use measures of carbon emissions, primary energy consumption, and CO2 reduction targets by country to quantify these risks. Our findings indicate that these risks are not systematically integrated into models that explain sovereign credit ratings.

In December 2015, at the UN Climate Change Conference (COP21) in Paris, 196 countries, including the US and all European countries in our sample, adopted a legally binding international commitment to limit the increase in global temperatures. The treaty was signed in April 2016 and ratified in November 2016 by all signatories. Given its significance in raising public awareness of the serious threat posed by climate change and the urgency of policy actions, it is reasonable to conjecture that climate change risks have been reassessed, and the associated higher transition costs have been incorporated into the models used by CRAs to evaluate sovereign creditworthiness, following the treaty's implementation.

Consequently, we define a natural experiment using the Paris Agreement as an exogenous event that may have shifted CRAs' assessments of climate-related risks and their relevance for sovereign creditworthiness (see, for example, Moody's Investor Service, 2021, Standard & Poor's, 2021).

Following the Paris Agreement, all major CRAs signed the UN Principles for Responsible Investments (PRI) in May 2016, committing to systematically and transparently evaluate the extent to which environmental factors are relevant to credit assessments for different issuers. They also pledged to review how these factors are integrated into credit analysis as their understanding evolves.

In the second stage of our analysis, we investigate whether there is evidence that the major CRAs have updated their models to reflect this commitment and whether climate risks are adequately considered in their credit ratings. Standard & Poor's, Moody's, Fitch Ratings, and DBRS Morningstar published several documents—including criteria and guidelines—to publicly affirm their recognition of ESG factors in credit risk analysis (see Standard & Poor's, 2021; Moody's Investor Service, 2021; Fitch Ratings, 2022; and DBRS Morningstar, 2021).[3]

To identify country exposures to physical and transition risks, we use the unique *Climate Change Risk Country Scoring Model* developed by the European Investment Bank (Ferrazzi et al., 2021),

[3]See Cantor and Packer (1995) for a description of the credit rating industry.

which ranks countries according to their climate change risks. We use these scores to divide the sample of countries into two groups according to their exposure to climate change risks. The median score determines which countries are classified as highly exposed (the treatment group) and which are low-exposed (the control group) to climate risk factors.[4] We employ a difference-in-difference methodology to assess whether there is evidence that CRAs have updated their assessment methodologies following the Paris Agreement and the UN PRI, attributing greater weight to climate risks for the treatment group, which is more exposed to these risks.

We find some partial evidence that CRAs attribute lower ratings to countries that are more exposed to physical risk relative to the control group after the Paris Agreement. This may reflect CRAs' acknowledgment that natural disasters—possibly on an increasing trend—can significantly impact sovereign balance sheets, particularly in low-income countries. Therefore, these risks should be properly accounted for in credit risk models. At the same time, we find evidence that CRAs have started to treat transition risk differently in their rating assessments after the Paris Agreement. In particular, countries exposed to transition risk receive higher ratings when they commit to more ambitious CO2 emissions reduction targets and decrease CO2 emission intensity after the accord.

In the final steps of our analysis, we consider specific country factors that may amplify or mitigate the effects of climate risk exposures. We examine sovereigns with high levels of debt, those highly reliant on fossil fuel revenues, and countries that derive revenues from commodities that may benefit from the green transition. We show that all these factors significantly influence sovereign ratings.

We run a series of additional checks to evaluate the robustness of our results. First, the break year may not necessarily have been in 2015, as the signing of the Paris Agreement was a process that extended beyond that year. CRAs may have front-loaded some of the treaty's effects by starting to review their assessment methodologies in anticipation of the treaty adoption. We run our model using a different break year—2016—and show that the results are robust to this change. Second, the results might be sensitive to the methodology used to identify treatment and control groups. As a robustness check, we identify the treatment group using the first quartile of the distribution of exposures instead of the median and find that the results are not significantly

[4] To assess the robustness of our analysis, we define the two groups using a number of different criteria, as detailed in the following sections.

affected by this choice. We also run several other sensitivity and robustness checks for the sample period; we use a shorter panel (2005-2021), and fit the model with and without country and year fixed effects and the advanced economy dummy. We include various specifications regarding the macroeconomic, fiscal, and institutional control factors for the sovereign rating equations. Overall, we find that the weak evidence for physical and transition risk remains robust across all alternative specifications.

Previous research on climate risks has primarily focused on corporate ratings and on physical risk for sovereigns. For instance, Carbone et al. (2021) examines how climate risk is included in corporate ratings. Recent studies have also explored the relationship between transition risks and corporate credit risk. Specifically, Faralli and Ruggiero (2022) show that firms with higher carbon emissions have a greater probability of default after the Paris Agreement, attributed to an increase in asset volatility among higher emitters. Cevik and Jalles (2023) investigate how physical risk influences sovereign credit ratings across a panel of 67 countries, finding that countries with high vulnerability receive, on average, lower ratings, while high resilience to climate risk is linked to higher credit scores. Consistently, Beirne et al. (2021) examine the impact of physical climate risk on the sovereign cost of borrowing for 40 advanced and emerging economies, showing that vulnerability has a negative and persistent effect on sovereign bonds yields, especially in countries highly exposed to physical risk. Similarly, Boitan and Marchewka-Bartkowiak (2022) finds that countries exposed to climate risk pay a higher risk premium on their sovereign debt.[5] Tran and Uzmanoglu (2024) examines US cities and finds limited evidence that their credit ratings take climate risk considerations into account. In De Angelis et al. (2024), the authors connect credible commitments to net-zero targets with financial stability for European countries.

Our study contributes to this literature in three key ways. First, we analyse sovereign ratings, which have received less attention than corporate credit ratings. Second, we examine physical risk alongside various measures of transition risk, introducing a novel measure based on the commitments under the Paris Agreement. Third, we use novel confidential indicators of country exposures to climate risks to identify the countries most affected by these risks. Our definition of a natural experiment using the Paris Agreement as an exogenous event for sovereign borrowers is a novel addition to the literature.

[5] See MSCI (2021) for a detailed discussion on how climate risk can affect bond pricing.

Our findings have important policy implications. If climate risks are explicitly considered in sovereign risk assessments, this could incentivise the *greening* of sovereign debt. Key metrics for evaluating these risks include CO2 emission intensities and indicators of vulnerability and readiness. Credit ratings play a crucial role in some central bank and regulatory policies, particularly concerning asset quality in banks' balance sheets. Therefore, including climate change risks in credit rating assessments will have indirect implications for these policies.

The rest of this paper is organised as follows. Section 2 describes the data. Section 3 outlines the empirical methodology and the identification strategy. Section 4 presents the results. Section 5 concludes.

2 Data

To conduct our analysis, we construct a database that collects information from four domains: a) sovereign ratings; b) macroeconomic data; c) climate variables; and d) exports of certain commodities. We estimate our models on ratings from 124 sovereigns over the period 1999-2021. The sample is diverse in terms of geographic composition, including 33 advanced economies, 62 emerging economies, and 29 low-income countries, making it suitable for analysing different types of physical and transition risks (see Figure 2). In this section, we provide an overview of the variables included in our model and their data sources. A detailed description of these variables can be found in Table 12 in the Appendix.

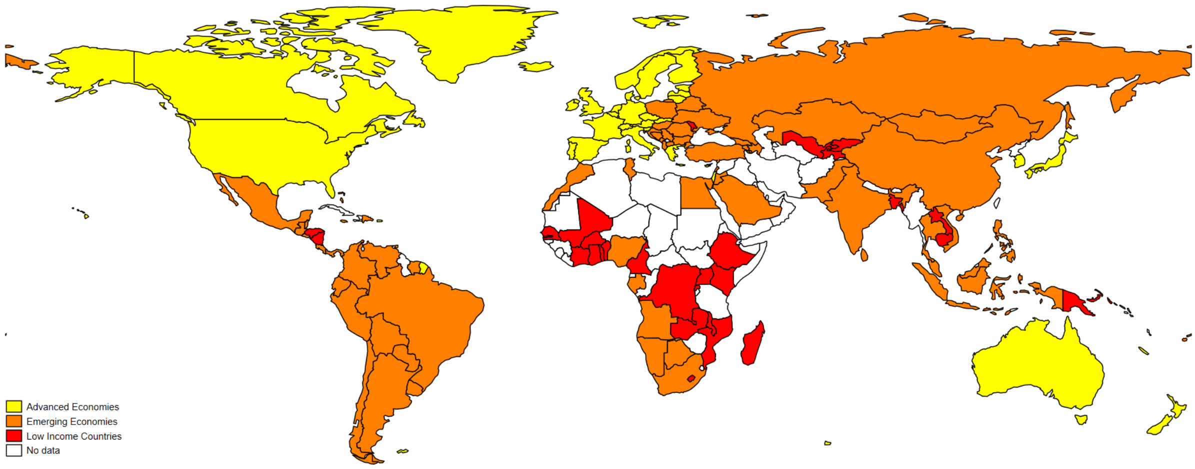

Figure 2: Countries included in the analysis. A total of 124 countries is included in the analysis: 33 advanced economies, 62 emerging economies, and 29 low-income countries.

2.1 Ratings data

The objective of our study is to model the series of foreign currency sovereign ratings issued by S&P, Moody's, Fitch, and DBRS. To ensure a consistent analysis across the methodologies of CRAs, we retrieve equivalent series for each agency. Table 10 in the Appendix provides a detailed description of the original series.

The main source for sovereign ratings data is the *Centralised Security Database* of the Eurosystem (CSDB). We select records for issuers classified as sovereign, based on ESA[6] and NACE[7] classifications and restrict our analysis to countries that are IMF members.[8]

CRAs use different rating scales. To combine information across these agencies, we convert ratings into numeric values from 1 to 21 according to the conversion scale illustrated in Table 11, where high (low) values represent high (low) ratings. Converted ratings are then arranged into an annual panel based on the following assumptions: if a rating is not revised for more than one year, it is considered constant; if a rating is revised multiple times over twelve months, the latest value is recorded for that year. Table 1 shows summary statistics for the sovereign ratings by type of economy. Credit ratings are generally consistent across agencies, with more pronounced differences observed for emerging economies and low-income countries.

Figure 3 illustrates the rating differences across agencies from 1980 to 2021. Approximately 90% of the ratings differ by less than two notches over the entire period. Consequently, we estimate our baseline models using the average ratings across agencies as the dependent variable.[9]

2.2 Macroeconomic data

The macroeconomic explanatory variables in our analysis are largely consistent with the model of Cantor and Packer (1996). We collect data for all countries with at least one sovereign rating record (see Section 2.1) to maximise time-country coverage. Any country missing from the selected series is excluded from the analysis.

The values of GDP per capita, GDP growth rate, gross domestic debt to GDP ratio, and current

[6]See this page for more information on ESA classification.

[7]See https://ec.europa.eu/competition/mergers/cases/index/nace_all.html.

[8]See this page for the full list of IMF countries.

[9]As a robustness check, we replicate most of our analysis using ratings from individual agencies. We find that results are broadly comparable to those obtained using average ratings for the four CRAs. However, when using ratings from individual agencies, the sample size may be significantly reduced in some cases.

Table 1
Average (first column), standard deviation (second column), minimum (third column), maximum (fourth column) and number of observations (fifth column) of Standard & Poor's, Moody's, Fitch, and DBRS foreign currency ratings broken down per type of economy. Data from 1999 to 2021.

	Mean	SD	Min	Max	N
Advanced Economies					
S&P	18.31	3.34	2	21	699
Moody's	18.10	3.58	1	21	736
Fitch	18.10	3.36	4	21	670
DBRS	18.16	3.97	4	21	240
Average	18.21	3.30	2.67	21	759
Emerging Economies					
S&P	10.12	3.30	1	18	1132
Moody's	11.12	3.40	2	18	451
Fitch	10.37	3.29	1	19	973
DBRS	12.76	3.37	1	18	113
Average	10.13	3.22	1	18.5	1261
Low Income Countries					
S&P	6.95	1.45	1	9	314
Moody's	6.21	1.83	2	9	63
Fitch	7.22	1.10	1	9	139
DBRS	.	.	.	.	0
Average	6.87	1.52	1	9	392
Total					
S&P	12.32	5.31	1	21	2145
Moody's	14.98	5.18	1	21	1250
Fitch	13.03	5.14	1	21	1782
DBRS	16.43	4.55	1	21	353
Average	12.14	5.24	1	21	2412

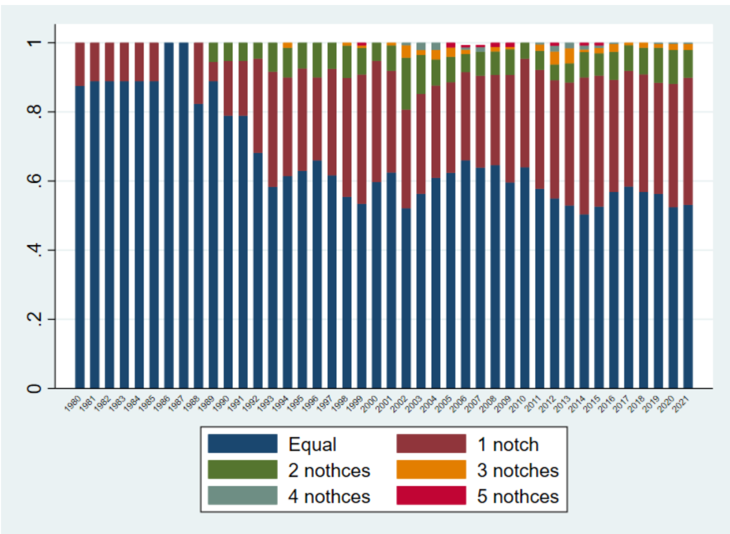

Figure 3: Rating Differences. Annual series showing the percentage of sovereign credit ratings from S&P, Moody's, Fitch, and DBRS that do not differ (blue), differ by 1 notch (brown), 2 notches (green), 3 notches (orange), 4 notches (light blue), and 5 notches (red). Data from 1980 to 2021.

account balance are sourced from the *World Economic Outlook* published by the International Monetary Fund (IMF) in October 2021. Inflation data is retrieved from the *International Financial Statistics* published by the IMF in January 2022. Data for external debt scaled by exports comes from two publications by the World Bank: for emerging economies, we use data from the *International Debt Statistics*; for advanced economies, we use external debt values published in the *Quarterly External Debt Statistics*, divided by exports level available in the *Balance of Payments Statistics*. Finally, the default indicator for each country is based on the amount of debt in default as reported in the *Sovereign Default Database*, jointly maintained by the Bank of Canada and the Bank of England.

In Section 4.3, we examine the role of high levels of indebtedness for countries highly exposed to climate risk. Our primary aim is to understand whether CRAs view countries with high debt levels as having higher credit risk when they are exposed to extreme weather events or when significant efforts are needed to transition to a greener economy. We calculate a measure of debt based on the gross domestic debt to GDP ratio and create a dummy variable, $HighDebt_{c,t}$, that takes the value of 1 if the debt to GDP ratio at time $t-1$ exceeds the median of the distribution for the years prior to 2016.

2.3 Climate data

Next, we outline the data used in our study to measure physical and transition climate risks for sovereigns.[10]

For physical risk, we consider temperature anomalies, changes in the number of disasters, and indicators of readiness and vulnerability.[11] Figure 4 displays temperature anomalies for the countries in our sample, grouped into advanced and emerging economies, relative to the baseline period (1951-1980).

For a given country c, we compute the percentage change in the number of disasters between time t and time $t-1$ as follows:

[10]Climate risk is traditionally categorised into physical risk and transition risk (BCBS, 2021). Physical risk refers to the economic costs of extreme weather events (acute physical risk), long-term gradual climate shifts (chronic physical risks) and indirect effects of climate change, such as the loss of ecosystem services. Transition risk pertains to the adjustments needed for a low-carbon economy and primarily concerns unexpected changes in policies or the preferences of consumers and investors. The literature identifies several transmission channels through which climate risks directly affect a country's ability to repay its debts. For a review, see Volz et al. (2020).

[11]Temperature anomalies data are available at: https://www.fao.org/faostat/en/#data/ET and are maintained by the Temperature Change domain.

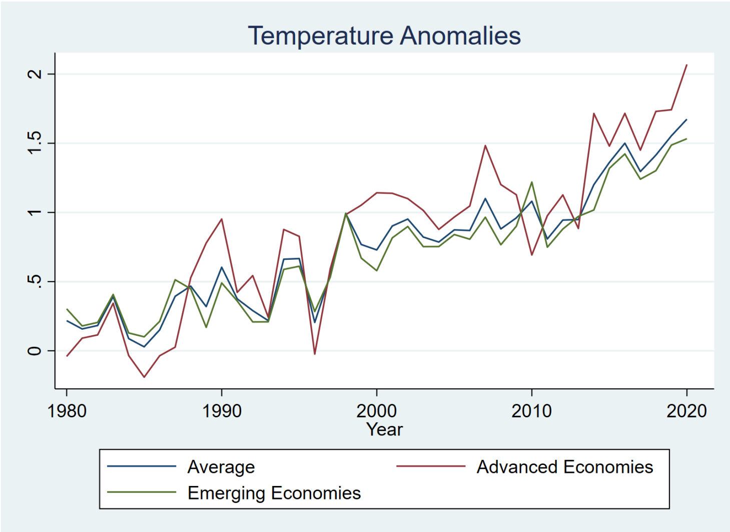

Figure 4: Temperature anomalies. Average temperature anomalies for advanced economies (red line), emerging economies (green line), and all countries (blue line). Temperature anomalies are defined as deviations from the respective average temperatures during the 1951-1980 period. Values in each group are weighted by country surface area. Data from 1980 to 2021.

$$\frac{(NumberOfDisasters_{c,t} - NumberOfDisasters_{c,t-1})}{NumberOfDisasters_{c,t-1}} \times 100$$

.

Additionally, we compute the number of disasters per square kilometer as:

$$\frac{NumberOfDisasters_{c,t}}{CountrySurface_{c,t}} \tag{1}$$

where $NumberOfDisasters_{c,t}$ is the sum of the number of floods, storms, droughts, wildfires and heat waves in country c in year t (see Figure 5).[12] If the duration of a natural disaster exceeds one year, that specific event is taken into account in multiple years. Raw data are from EM-DAT, the International Disaster Database, available at https://www.emdat.be/.

Measures of *Readiness* and *Vulnerability* are sub-components of the ND-GAIN indicator published by the University of Notre Dame. *Readiness* reflects a country's ability to face extreme events, while *Vulnerability* indicates a country's predisposition to be affected by these climate

[12]Data for country surface are from the World Development Index by the World Bank and available at https://datatopics.worldbank.org/world-development-indicators/.

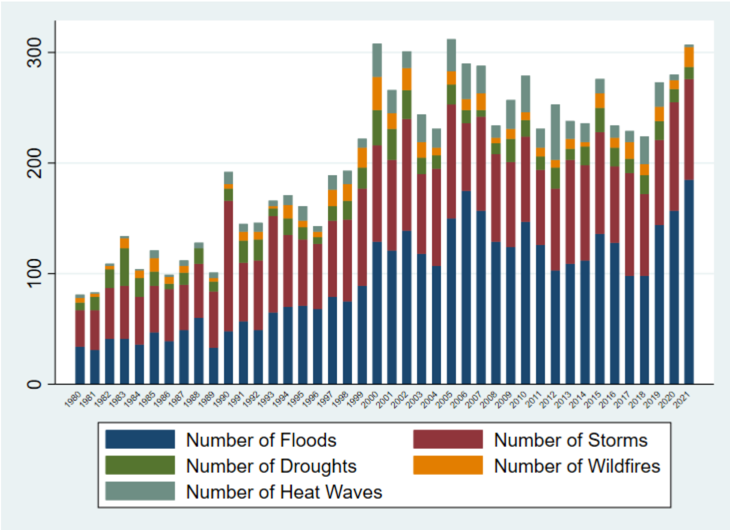

Figure 5: Total natural disasters per year. Number of floods, storms, droughts, wildfires, and heat waves reported in all the countries in our sample in a given year. If the duration of a natural disaster exceeds one year, the event is counted in multiple years. Data from 1980 to 2021.

events.[13]

For transition risk, we include two backward-looking indicators and one forward-looking indicator. Specifically, we consider the intensity of carbon emission (Figure 6), primary energy consumption per unit of GDP, and the percentage reduction in CO2 emissions under the target achievement scenarios compared to the business-as-usual scenario. The first two indicators are considered in both absolute levels and percentage annual changes, and they are sourced from the Our World in Data database.[14]

Our third indicator is computed as follows:

$$\frac{(CO2Emissions2050_{c,bau} - CO2Emissions2050_{c,target})}{CO2Emissions2050_{c,bau}} \times 100 * Ratification_{c,t}$$

where $CO2Emissions2050_{c,bau}$ and $CO2Emissions2050_{c,target}$ are IMF estimates for CO2 emissions in the business-as-usual scenario and the Paris Agreement target achievement scenario, respectively, as stated in the Nationally Determined Contributions for each country c. $Ratification_{c,t}$ is a dummy variable that takes the value of 1 for country c if t is equal to, or greater than, the year in which the agreement was ratified by that country.

[13] Available at https://gain.nd.edu/our-work/country-index/.
[14] See https://ourworldindata.org/.

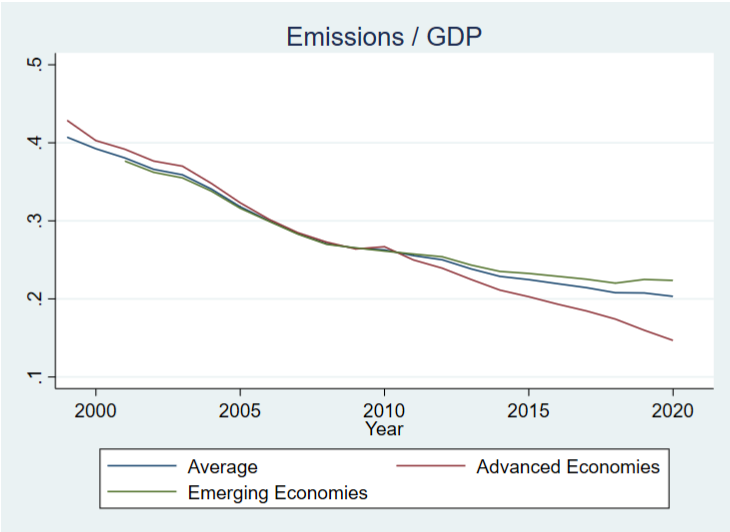

Figure 6: CO2 emission intensity per unit of GDP. The figure shows advanced economies (red line), emerging economies (green line), and all countries combined (blue line). Data from 1995 to 2021.

Finally, scores for physical and transition risk exposures are derived from the series of exposures provided by the EIB, and discussed in Ferrazzi et al. (2021).

2.4 Data on fossil fuels and transition-critical materials

The transition to a greener economy involves a gradual reduction in fossil fuel use. Initially, natural gas is likely to play a significant role in energy production, substituting for more polluting fossil fuels such as coal and oil. In subsequent phases, countries will need to move away from fossil fuels and switch to cleaner energy sources such as renewables. In this context, certain materials will likely increase in value, particularly those required for renewable energy production and battery manufacturing. Against this background, Section 4.3 investigates whether the current reliance on fossil fuels or transition-critical material influences the assessment of sovereign credit ratings and how this depends on the countries' exposures to climate risks.

We collect data on fossil fuels exports (oil, coal, and gas) and calculate their percentage relative to total merchandise exports, using data published by the World Bank. Additionally, we retrieve data on fossil fuel rents, which measure the net revenues arising from the production of oil, coal, and gas. We compute indicators of each country's reliance on fossil fuels by selecting the top 20 top exporters in each year. We also construct a dummy variable that takes value one if country c in year t is among the top 20 countries with the highest values for fossil fuel rents. We produce two alternative measures based on the total value of fossil fuel rents, and fossil fuels excluding gas.

Similarly, we retrieve a time series for exports of transition-critical materials. We focus on the seven commodities identified by Miller et al. (2023) as particularly important for the green transition: copper, graphite, nickel, manganese, cobalt, lithium, and rare earths. We then calculate the share of these exports relative to total exports and derive indicators that describe the relative importance of these materials in each country. Data are sourced from the World Bank.

3 Estimation and identification

In this section, we present our modeling and identification approach. We begin from the canonical ratings model of Cantor and Packer (1996) as the foundation for our empirical estimation, and add climate variables to assess whether they enhance the accuracy of the basic model. Our estimation strategy unfolds in several steps. First, we estimate the following panel regression model over the full sample period, augmented with climate variables:

$$Rating_{i,t} = \alpha + \beta ClimateVariable_{i,t-k} + \nu X_{i,t-1} + \phi_i + \theta_t \tag{2}$$

.

In this equation, the dependent variable is the average foreign currency credit rating at time t for country i, calculated across the four CRAs considered. The term $X_{i,t-1}$ includes the control variables by country, largely following the approach of Cantor and Packer (1996) with a one-year lag. Specifically, we include log GDP per capita, GDP growth, inflation, debt to GDP ratio, current account balance to GDP ratio, external debt to exports ratio, a default indicator, and a dummy variable to distinguish between advanced and emerging economies. The variable $ClimateVariable_{i,t-k}$ relates to physical or transition risk, observed with lag of 0 or 1 ($k = 0, 1$) depending on the measure. Additionally, country (ϕ_i) and time (θ_t) fixed effects are included in most specifications.

In the second step, we test whether climate risk has been incorporated in sovereign ratings following the Paris Agreement, when several CRAs publicly committed to updating their models to include climate risks in their credit rating assessment processes. We use the Paris Agreement in 2015 as an exogenous shock, separating countries into treatment and control groups based on their exposure to climate risks. The assumption is that the sovereign ratings of countries in the treatment group, which are more exposed to climate risks, will be more affected by the treaty, resulting in a comparatively greater decrease in their ratings than those of the countries in the control group. We estimate several specifications of a triple difference-in-differences model with one continuous treatment as follows:

$$\begin{aligned}
Rating_{i,t} =& \alpha + \beta ClimateVariable_{i,t-k} + \gamma PostPA + \delta Treatment_i + \omega Treatment_i * PostPA + \\
& \upsilon Treatment_i * ClimateVariable_{i,t-k} + \eta PostPA * ClimateVariable_{i,t-k} + \\
& \lambda Treatment_i * PostPA * ClimateVaribale_{i,t-k} + \nu X_{i,t-1} + \phi_i + \theta_t
\end{aligned} \tag{3}$$

where $Treatment_i$ is a variable identifying countries that are more exposed to physical or transition risk in the various specifications. Identification of the treatment and control groups relies on the *EIB climate ratings for physical and transition risk* described in Ferrazzi et al. (2021). $PostPA$ is a dummy variable that takes the value of one for years after the Paris Agreement entered into force at the end of 2015 (i.e., from 2016 onwards in our analysis). We also consider interactions with variables measuring specific exposures to climate risks.

To further advance our analysis, we evaluate whether countries highly reliant on revenues from fossil fuels experience a decrease in credit ratings after the Paris Agreement, based on the premise that fossil fuels (such as oil or coal) are expected to be phased out to achieve net-zero goals. At the same time, the transition to a greener economy is likely to create a comparative advantage for countries with high reserves of the so called *transition-critical materials*. For instance, commodities used in the manufacture of batteries or devices producing renewable energy are anticipated to see increased demand due to the collective need to move away from traditional energy sources (Bain, 2021). Consequently, we assess the extent to which these considerations are included in credit rating assessment of major CRAs.

We implement a difference-in-differences strategy that includes indicators of fossil fuel and transition-critical materials. For the former, we identify measures of exports and rents, both including and excluding gas, acknowledging that natural gas is likely to play a role in the initial phase of the transition, when more emission-intensive fossil fuels will be gradually phased out. For the latter we draw on the findings of Miller et al. (2023), which identify seven commodities expected to see increasing demand due to the shift towards greener energy sources. Specifically, we examine whether the share of exports of copper, graphite, manganese, nickel, cobalt, lithium, and rare earths is considered in the credit rating assessment, following the intuition that countries exporting these materials will be better positioned in the future, given the current state of technology.

To evaluate the incidence of fossil fuel reliance and transition critical material exports, we estimate the following model:

$$\begin{aligned} Rating_{i,t} =& \alpha + \beta CommodityExposure_{i,t-k} + \gamma PostPA + \delta Treatment_i + \omega Treatment_i * PostPA + \\ & \upsilon Treatment_i * CommodityExposure_{i,t-k} + \eta PostPA * CommodityExposure_{i,t-k} + \\ & \lambda Treatment_i * PostPA * CommodityExposure_{i,t-k} + \nu X_{i,t-1} + \phi_i + \theta_t \end{aligned} \tag{4}$$

where $CommodityExposure_{i,t-k}$ is a continuous or dummy variable representing the exposure of country i to fossil fuels or transition critical materials at time t or $t-1$, depending on the specification. We use six different measure of fossil fuel reliance: three continuous indicators, and three binary indicators, along with various definitions of economic reliance on transition-critical materials.

First, we assess the importance of revenues from fossil fuels for country i at time $t-1$. We use three definition of this indicator. First, we examine the share of fossil fuel exports in total exports. Second, we analyse the value of fossil fuel rents, including and excluding gas, as a percent of GDP. Additionally, we account for a time-invariant dummy variable that takes the value of one if the country highly relies on fossil fuels in terms of exports or rents. We propose three specifications for this dummy. A country is considered fossil fuel reliant if its median ranking for fossil fuel exports to total exports over the period 1999-2015 is 20 or lower. In other words, if a country consistently ranked among the top 20 fossil fuel exporters before 2015, it is classified as a fossil fuel exporter. We compute a similar measure based on fossil fuel rents, both including and excluding gas. The treatment groups are defined using the top quartile of countries exposed to physical and transition risk, respectively.

In the next step, we evaluate the relevance of transition critical materials employing four continuous indicators. For each country i, we define exports of the seven transition-critical material as the percentage share of total export of country i and as their share of global exports of these materials in each year. We take these indicators with a lag, both in levels and as year-on-year change. In these specifications we explore three different treatment assignments: exposure to physical, transition, and climate risks, using the median of EIB scores.[15]

Our last analysis examines whether the level of public debt affects the ratings of countries exposed to climate risks, particularly whether CRAs assign lower ratings to highly indebted sovereigns facing adverse climate events, or those further from achieving the Paris Agreement goals. Climate risks could be more relevant for highly indebted countries with lower fiscal capacity to address the costs of the green transition. To check whether the exposure to climate risk is amplified by very high levels of debt, we estimate four separate difference-in-difference equations where we assume that sovereigns with higher debts would have lower ratings after the Paris Agreement. Specifically, we estimate the following model:

$$Rating_{i,t} = \alpha + \beta HighDebt_i + \gamma PostPA + \eta PostPA * HighDebt_i + \nu X_{i,t-1} \tag{5}$$

where $X_{i,t-1}$ is the matrix of controls inspired by Cantor and Packer (1996) taken with a lag.[16] $HighDebt_i$ is a dummy variable that takes the value of one if the level of debt to GDP ratio of country i in 2015 is above the median of the distribution of debt-to-GDP ratio computed for the years up to 2015. To take into account that advanced and emerging economies may have different debt tolerance, we compare the debt to GDP ratio in 2015 of advanced and emerging countries to the median value for advanced and emerging economies respectively. We estimate the model over a) the full sample, b) countries exposed to physical risk, c) countries not exposed to physical risk, d) countries exposed to transition risk, and e) countries not exposed to transition

[15]Countries exposed to climate risk are those for which either the physical risk or the transition risk scores are above the median.

[16]In these specifications, we exclude the dummy variable distinguishing advanced and emerging economies to avoid multicollinearity.

risk.

4 Results

4.1 Panel Regressions

Following Cantor and Packer (1996), we begin by estimating a baseline panel model to explain sovereign credit ratings with a sample of macroeconomic and financial variables. Table 13 in the Appendix presents the results of these estimations. All explanatory variables have statistically significant coefficients, except for the current account balance, which we still include in the estimation for comparison with the previous literature.

Table 2
Results of the panel regressions in Equation 2 for 124 countries from 1999 to 2021, based on Cantor and Packer (1996) and augmented for physical risk variables. Macroeconomic and financial determinants of credit ratings included in the estimations are not reported in the table.

	Rating				
	(1)	(2)	(3)	(4)	(5)
Temperature Anomalies t-1	-0.148*				
	(0.0765)				
Percentage Change in Disasters t-1		-0.000441*			
		(0.000261)			
Number of Disasters per Sq. Km t-1			-237.7		
			(207.5)		
Vulnerability				3.807	
				(10.20)	
Readiness					8.981***
					(2.057)
Observations	2,000	2,013	2,013	1,882	1,888
R-squared	0.956	0.956	0.956	0.957	0.960
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, we augment the analysis with measures of climate risks, first focusing on physical risk and then on transition risk. Table 2 presents the results of the panel estimations when physical risk measures are included in the base model. The inclusion of these variables does not change the economic and statistical significance of the coefficients of the macroeconomic and financial variables. For clarity, we report only the coefficients related to climate risk in the table.

We consider three measures of physical climate risk: temperature anomalies, changes in the occurrence of natural disasters, and the number of natural disasters per unit of surface. The results in columns 1 and 2 of the table show that the coefficients for two of these measures are statistically significant and negative. Higher temperature anomalies and an increased occurrence of natural disasters are generally associated with lower credit ratings. However, the magnitude of these coefficients is not high, implying that the economic effects are negligible.

We also include indicators of country vulnerability and readiness for physical climate risk (see Section 2.3). The coefficient for the readiness indicator is highly statistically significant and positive (see column 5 in Table 2), implying that countries better equipped to manage physical risk tend to have higher credit ratings. However, we note that in the estimation, the coefficient of the Economy dummy (advanced vs emerging economies) loses statistical significance, likely due to its high correlation with the readiness indicator. Overall, our findings suggest that CRAs consider physical risk when assessing sovereign ratings, but its impact is modest.

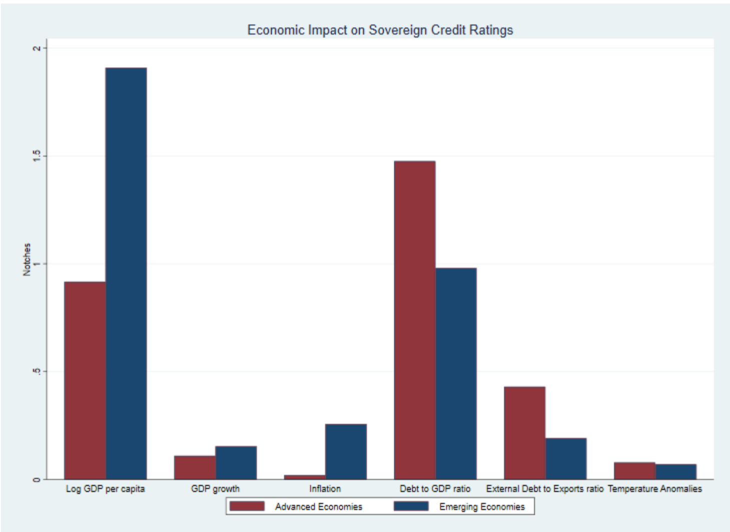

Figure 7: Economic impact of physical risk on sovereign ratings. Absolute value of the effect of one (1% Winsorized) standard deviation shock of macroeconomic and climate risk variables on sovereign credit ratings for advanced (red) and emerging (blue) economies.

Figure 7 illustrates the economic significance of physical risk in the assessment of sovereign ratings, specifically highlighting the contribution of temperature anomalies. While this risk is statistically significant in the estimated models, its economic importance is relatively minor compared to other factors, such as measures of economic growth and sovereign debt. This is consistent with the stated approach of CRAs, which claim to consider risks to sovereigns over a limited time horizon—typically around five years.

Transition risk is generally harder to measure for sovereigns. As a proxy for this risk, we consider various combinations of measures of country carbon emissions and energy use: emission intensities (both level and growth), energy consumption (both level and growth), and CO2 reduction targets. Results are presented in Table 3. None of the coefficients for these measures are statistically significant, suggesting that transition risk—at least as measured by these proxies—is not reflected in the models for sovereign ratings.

Table 3
Results of the panel regressions in Equation 2 for 124 countries from 1999 to 2021, based on Cantor and Packer (1996) and augmented for transition risk variables. Macroeconomic and financial determinants of credit ratings included in the estimations are not reported in the table.

	Rating				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity t-1	-0.744 (0.544)				
Primary Energy Consumption to GDP ratio t-1		0.0198 (0.238)			
CO2 Reduction Target			0.769 (0.525)		
Emission Intensity Growth t-1				0.000836 (0.00343)	
Primary Energy Consumption to GDP ratio Growth t-1					0.000300 (0.00399)
Observations	2,013	1,969	2,013	2,013	1,969
R-squared	0.956	0.957	0.956	0.956	0.957
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results of the model estimations that include both physical and transition risks are generally robust to the exclusion of country fixed effects.[17] For robustness, we also estimate the models using only ratings issued by a single credit rating agency at the time. The results indicate that all agencies consider at least one measure of physical risk when assessing sovereign ratings. Conversely, transition risk is generally not considered.[18] The results remain robust even when weighted by GDP in US dollars (see Tables 19, and 20 in the Appendix).

[17]The coefficient for the percentage change in the number of disasters (column 2 in Table 2), which is not particularly high in absolute value, is the only one that becomes statistically insignificant when country fixed effects are removed.

[18]Results are available upon request. Notice that the number of observations for DBRS is relatively small, and individual estimates for this agency may not be exhaustive.

Tables 15, 16, 17, and 18 in the Appendix present results for these models estimated separately for EU and non-EU countries, as well as for advanced and emerging economies. The significant effect of temperature change appears to be driven primarily by EU countries and advanced economies. In contrast, the year-on-year change in the number of extreme weather events seems to negatively impact mainly emerging economies and non-EU countries.

From these results, we conclude that within physical risk, chronic risk is primarily driven by advanced economies, while acute risk is more pronounced in emerging economies. This distinction is supported by the fact that advanced economies typically have higher ability to manage extreme climate events, whereas emerging economies face larger challenges in addressing humanitarian crises and reconstruction following natural disasters. There is also some evidence that energy consumption per unit of GDP is a relevant factor for CRAs when assessing advanced economies.

4.2 The Paris Agreement

The Paris Agreement marked a pivotal moment in the global response to climate change, significantly impacting the financial sector.[19] Immediately after the Paris Agreement, CRAs pledged to better integrate climate factors in their sovereign rating assessments.[20] In this section, we examine the extent to which CRAs have reviewed their assessment frameworks for sovereign ratings to assign greater weight to climate-related risks after the Agreement.

To address this issue, we estimate several specifications of a difference-in-differences model, as shown in Equation 3. The identification strategy for the treatment and control groups is based on the scores developed by Ferrazzi et al. (2021). The country scores for physical risk exposure account for acute risk, chronic risk, and adaptation capacity. The scores for transition risk exposure consider fossil fuel rents, GHG emissions, energy consumption, renewable production, and climate ambition. We split the countries in our sample in two groups (treatment and control) using the median scores for physical and transition risk exposure in their respective analysis.

Results are shown in Table 4, where we report only the coefficients of the interaction coeffi-

[19]The only countries that have not formally ratified the Paris Agreement are Iran, Libya, and Yemen. These countries are excluded from our sample. The United States is the only country to have withdrawn (twice) from the agreement. However, we keep this country in our sample.

[20]CRAs have developed new methodologies to include climate risks in their assessments of both corporate and sovereign credit ratings. For an analysis of corporate credit ratings, see Carbone et al. (2021).

Table 4
Results of the difference-in-differences estimations of Equation 3 for temperature anomalies, number of natural disasters per squared kilometer, and readiness. Sample period is from 1999 to 2021. The macroeconomic and financial determinants of credit ratings included in the estimations are not reported in the table.

		Rating	
	(1)	(2)	(3)
Exposed to Physical Risk x Post Paris Agreement	-0.202	-0.635***	0.180
	(0.600)	(0.247)	(1.069)
Temperature Anomalies t-1 x Exposed to PR x Post PA	-0.364		
	(0.399)		
Number of Natural Disasters per Sq. Km t-1 x Exposed to PR x Post PA		-212.5	
		(433.9)	
Readiness x Exposed to PR x Post PA			-1.336
			(2.174)
Observations	2,000	2,013	1,888
R-squared	0.957	0.957	0.961
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5
Results of the difference-in-differences estimations of Equation 3 for emission intensity, primary energy consumption to GDP ratio (both levels and percentage growth), and CO2 emission reductions under target achievement scenarios. Sample period is from 1999 to 2021. The macroeconomic and financial determinants of credit ratings included in the estimations are not reported in the table.

			Rating		
	(1)	(2)	(3)	(4)	(5)
Exposed to Transition Risk x Post Paris Agreement	0.0445	0.291	-0.149	-0.0942	-0.191
	(0.408)	(0.585)	(0.238)	(0.229)	(0.243)
Emission Intensity t-1 x Exposed to TR x Post PA	-2.459				
	(1.930)				
Primary Energy Consumption to GDP ratio t-1 x Exposed to TR x Post PA		-0.726			
		(0.523)			
Emission Intensity Growth t-1 x Exposed to TR x Post PA			-0.0234*		
			(0.0125)		
Primary Energy Consumption to GDP ratio Growth t-1 x Exposed to TR x Post PA				-0.00548	
				(0.0164)	
CO2 Reduction Target x Exposed to TR					1.465*
					(1.025)
Observations	2,013	1,969	2,013	1,969	2,013
R-squared	0.957	0.957	0.956	0.957	0.957
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

cients of interest. We find partial evidence that CRAs attribute lower ratings to countries that are more exposed to physical risk relative to the control group after the Paris Agreement, as indicated by the interaction coefficient in Column 3. However, when considering interactions with other measures of physical risk after the Paris Agreement, the coefficients are generally not significant.[21]

We assess the robustness of our results using two alternative identification strategies for countries highly exposed to physical risk. First, we consider the top 25% most exposed countries based on the EIB scores. Second, we identify exposed countries by selecting the top quartile of EIB scores for advanced and emerging economies separately. Our analysis confirms that even under these two alternative specifications, there is only partial evidence that CRAs have assigned greater weight to physical risk in their sovereign ratings assessments following the Paris Agreement.

We estimate a similar model using the scores for exposure to transition risk (see Table 5). When examining the coefficients of the triple interactions with transition risk scores, the post-Paris Agreement dummy, and measures of transition risk, we find that the coefficient for the change in CO2 emission intensity is negative and significant. This result suggests that CRAs may have started to treat transition risk differently in their rating assessments after the Paris Agreement. Also, countries exposed to transition risk with higher CO2 emission reduction targets appear to receive higher ratings after the Agreement.

Similarly to what was done for physical risk, we consider two alternative identification strategies for countries exposed to transition risk. First, we identify the top quartile of exposure to transition risk based on EIB scores. Second, we select the treated units as the top quartile of EIB scores for transition risk for advanced and emerging economies separately. In this case, results are robust across all specifications, indicating that increases in CO2 emissions negatively affects ratings after 2015.

For both analyses (including physical and transition risks), we estimate the models over a shorter time window (from 2005 to 2021) to determine whether the results are driven by older observations in the sample. The results remain largely unchanged with the shorter time series. Finally, we consider that the *pricing* of the Paris Agreement in credit ratings may have been delayed,

[21] The coefficients of temperature anomalies and the readiness indicator are statistically significant, with negative and positive signs respectively, but do not change after the Paris Agreement.

thus setting the break year to 2016 in the difference-in-differences strategy. Again, the results remain largely unchanged.

Overall, our findings suggest that before the Paris Agreement, CRAs paid some attention to physical risk in their rating assessments but largely overlooked transition risk. However, the situation appears to have changed since 2015, with evidence indicating that CRAs are now placing greater emphasis on physical risk in their assessments and have begun to consider transition risk as well in their rating models. This shift is evidenced by the significant role of Nationally Determined Contributions—a proxy for a country's ambition in the transition—as empirical determinant of sovereign ratings.

4.3 Reliance on fossil fuels, transition-critical materials, and fiscal capacity

Our previous analysis indicates that while climate risks are receiving increasing attention from CRAs, they still hold limited economic significance for sovereign ratings. However, specific country factors may significantly amplify or mitigate the impact of climate risk exposures on these ratings. In this section, we explore three features related to government balance sheets that may affect the interaction between sovereign ratings and climate risks.

First, we examine countries particularly exposed to climate change risks due to their reliance on fossil fuels revenues, including exports. The transition to a green economy may lead to shifts in consumption from some fossil fuels, such as oil and coal, to others like natural gas. Consequently, assessing the overall impact on countries heavily reliant on these revenues can be challenging. We use two different measures of reliance on fossil fuels revenues: the value of fossil fuel exports and the value of fossil fuels rents (see Table 12 in the Appendix). The latter measure is more comprehensive, as it represents the overall net revenues from fossil fuel extraction. Furthermore, fossil fuel rents can be disentangled between rents arising from oil, gas, and coal and rents arising only from oil and coal.

We estimate our baseline models in Equation 4 using two measures: 1) the top 20 countries as exporters or renters; and 2) the value of exports relative to total exports and rents relative to GDP. Tables 6 presents the coefficients for the interactions between the scores of exposure to physical (PR) and transition (TR) risks, reliance on fossil fuel revenues, and the Post-Paris

Agreement (PA) dummy.[22]

In most specifications, the values are negative and statistically significant. Sovereigns that rely on fossil fuel revenues and are exposed to both physical and transition risks experience lower ratings after the Paris Agreement. However, we do not find significant evidence that this is solely attributable to revenues from oil and coal.

Next, we consider countries that are major exporters of commodities expected to be significantly affected by the green transition. We focus on the top seven transition-critical materials identified by Miller et al. (2023): copper, graphite, nickel, manganese, lithium, cobalt, and rare earths. We construct four indicators to assess reliance on revenues from these commodities.

First, we create an aggregate indicator by summing the ratios of these commodities to total exports. Second, we analyse the exports of these transition critical materials for country i as a share of global exports of these commodities. We consider these indicators with a lag, both in levels and annual changes. Table 7 presents the results of estimating Equation 4, where we report only the coefficients of the interactions between the measures of commodity exports, the Post PA dummy, and the treatment dummy. In turn, we define the treatment dummy in three ways. First, we consider countries with a physical risk score above the median. Second, we do the same for transition risk score. And third, we define countries generally exposed to climate risks as the union of these two groups. There is evidence that countries exposed to climate risks receive higher ratings if they have greater exports of transition-critical materials, whether in terms of total exports or as a significant portion of global exports of these commodities. Additionally, increasing export levels seem to positively impact the credit ratings of these countries.[23]

Last, we examine the amount of outstanding sovereign debt. If a country is highly indebted, it is reasonable to assume that CRAs may evaluate the associated climate risks more rigorously. When a country's fiscal capacity is constrained by high levels of debt, its policy options to mitigate the impacts of increasing physical risk and to fund the green transition may be limited.

[22] We consider countries that depend on fossil fuel revenues and are also highly exposed to physical and transition risks, as measured by the top quartile of the EIB scores.

[23] Results are significant when considering countries generally exposed to climate risk as the treatment group. It is important to note that these commodities are exported only by a handful of countries, and the subsets exposed solely to physical and transition risks are modest. Therefore, it is not surprising that our estimations using different definitions of the treatment group yield at times insignificant coefficients, even though the majority of those coefficients are positive, indicating a potential small sample problem.

Table 6
Estimation results for difference-in-differences specifications of Equation 4 for physical (rows 1, 2, and 3) and transition (rows 4, 5, and 6) risk exposures, augmented with information on fossil fuel reliance. The coefficients represent triple interactions among exposure dummies, the post PA dummy, and indicators of fossil fuel reliance. In turn, fossil fuel reliance is measured: in Panel 1, with time-invariant dummies defined as: top 20 fossil fuels exporter, and the top 20 based on fossil fuels rents, both including and excluding gas; and in Panel 2, using the value at $t-1$ of the share of fossil fuel exports over total exports, and fossil fuel rents, including and excluding gas, as a percentage of GDP.

Panel 1

	Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
PR Exposed x Post PA x Top 20 FF exporter	-1.717*					
	(0.930)					
PR Exposed x PostPA x Top 20 FF renter (Oil, Coal, Gas)		-2.264***				
		(0.803)				
PR Exposed x PostPA x Top 20 FF renter (Oil, Coal)			-1.361			
			(0.929)			
TR Exposed x Post PA x Top 20 FF exporter				-1.477*		
				(0.766)		
TR Exposed x PostPA x Top 20 FF renter (Oil, Coal, Gas)					-1.895***	
					(0.657)	
TR Exposed x PostPA x Top 20 FF renter (Oil, Coal)						-2.077***
Observations	2,013	2,013	2,013	2,013	2,013	2,013
R-squared	0.957	0.957	0.957	0.957	0.957	0.957
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel 2

	Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
PR Exposed x PostPA x FF exports (% of total Export)	-0.0233**					
	(0.00960)					
PR Exposed x PostPA x FF rents (% of GDP, Oil, Coal, Gas)		-0.146**				
		(0.0699)				
PR Exposed x PostPA x FF rents (% of GDP, Oil, Coal)			-0.148*			
			(0.0803)			
TR Exposed x PostPA x FF exports (% of total Export)				-0.0143		
				(0.0102)		
TR Exposed x PostPA x FF rents (% of GDP, Oil, Coal, Gas)					-0.110**	
					(0.0437)	
TR Exposed x PostPA x FF rents (% of GDP, Oil, Coal)						-0.107**
						(0.0486)
Observations	1,904	1,973	1,975	1,904	1,973	1,975
R-squared	0.958	0.958	0.958	0.959	0.958	0.958
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7
Estimation results for the difference-in-differences specifications of Equation 4 for climate (rows 1 and 2), physical (rows 3 and 4) and transition (rows 5 and 6) risk exposures, augmented with information on transition-critical commodities exports. The coefficients represent triple interactions among exposure dummies, post PA dummy, and indicators of transition-critical commodities exports. In Panel 1, transition-critical commodities exports are measured as the percentage share of a country's exports in both levels (columns 1, 3, and 5) and year-on-year changes (columns 2, 4, and 6). In Panel 2, transition-critical commodities exports are measured as the percentage share of global exports in levels (columns 1, 3, and 5) and year-on-year changes (columns 2, 4, and 6).

Panel 1

	Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
PR or TR Exposed x PostPA x TCM exports (% of total country export)	5.170*					
	(2.810)					
PR or TR Exposed x PostPA x change in TCM exports (% of total country export)		0.0203***				
		(0.00515)				
PR Exposed x PostPA x TCM exports (% of total country export)			3.073			
			(3.657)			
PR Exposed x PostPA x change in TCM exports (% of total country export)				-0.00904		
				(0.0135)		
TR Exposed x PostPA x TCM exports (% of total country export)					2.435	
					(2.769)	
TR Exposed x PostPA x change in TCM exports (% of total country export)						0.00600
						(0.00906)
Observations	2,013	1,436	2,013	1,436	2,013	1,436
R-squared	0.957	0.965	0.957	0.965	0.957	0.965
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel 2

	Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
PR or TR Exposed x PostPA x TCM exports (% of global TCM export)	11.06					
	(7.899)					
PR or TR Exposed x PostPA x change in TCM exports (% of global TCM export)		0.0185***				
		(0.00478)				
PR Exposed x PostPA x TCM exports (% of global TCM export)			3.046			
			(16.22)			
PR Exposed x PostPA x change in TCM exports (% of global TCM export)				-0.00866		
				(0.0123)		
TR Exposed x PostPA x TCM exports (% of global TCM export)					9.103	
					(7.278)	
TR Exposed x PostPA x change in TCM exports (% of global TCM export)						0.00548
						(0.00871)
Observations	2,013	1,436	2,013	1,436	2,013	1,436
R-squared	0.958	0.965	0.958	0.965	0.958	0.965
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8
Estimation coefficients for the double interactions between post-Paris Agreement dummy and the High Debt dummy. Results for the model in Equation 5 are fitted on: the full sample (Column 1), countries exposed to physical and transition risks (Columns 2 and 3), and countries not exposed to physical and transition risks (Columns 4 and 5), respectively. The High Debt dummy is equal to one for country i if its Debt/GDP ratio in 2015 was above the median of the Debt/GDP ratio distribution computed for the years prior to 2016. Advanced and emerging economies are compared to the median computed for their respective groups. In this specification, we include all controls specified in the base model, except for the type of economy dummy to avoid multicollinearity.

	Rating				
	Full Sample (1)	PR exposed (2)	TR exposed (3)	PR not exposed (4)	TR not exposed (5)
High Debt x Post PA	-1.161*** (0.317)	-1.941*** (0.492)	-1.817*** (0.460)	-0.240 (0.312)	-0.500 (0.422)
Observations	2,013	906	1,012	1,107	1,001
R-squared	0.798	0.531	0.782	0.812	0.837
Country FE	NO	NO	NO	NO	NO
Year FE	NO	NO	NO	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We estimate our baseline model around the Paris Agreement, where identification is now provided by a variable measuring a country's indebtedness. Table 8 presents the results from the model specified in Equation 5. The variable High Debt is a dummy equal to 1 for countries with a debt-to-GDP ratio above the median calculated from years up to 2015 for both advanced and emerging economies.[24] For clarity, we report only the coefficients of the interaction between the Post PA dummy and the High Debt measure.

The first row of the table shows that countries with high levels of sovereign debt generally receive lower credit ratings after 2015, following the Paris Agreement. This finding is consistent across all specifications. To further investigate the relationship between sovereign debt and climate risks, we separately estimate the model for countries exposed to climate risks versus those not exposed, considering both physical and transition risks. The results in columns two and three of Table 8 indicate that the credit ratings of highly indebted countries exposed to climate risks are lower after the Paris Agreement. Thus, a high level of sovereign debt amplifies the effects of climate risk exposures. The significant coefficient supports the notion that managing the costs of the green transition may be more challenging for countries with substantial sovereign debt,

[24]Results are qualitatively similar if we use the highest quartile of the debt distribution, but we estimate the model separately for developed and emerging economies, consider the median of the overall debt distribution, and analyse the debt-to-GDP ratio.

regardless of their specific exposure to climate change risks.

5 Conclusions

The transition to a sustainable economy is a top priority for most governments and international institutions worldwide. However, it remains unclear how the costs associated with this transition should be evaluated and whether the current assessments of country risk adequately reflect these costs.

We analyse sovereign credit ratings for a large sample of countries, including both advanced and emerging economies. Our findings indicate that physical risk is reflected in sovereign credit rating evaluations, while there is no evidence that transition risk is included in these ratings.

Using the Paris Agreement as a natural experiment, we examine whether CRAs have updated their assessment models to account for the costs associated with the green transition. We find that countries more exposed to physical risk have received comparatively lower ratings after 2015. Additionally, CRAs appear to assign higher ratings to countries exposed to transition risk with more ambitious CO2 emission reduction targets and those that decrease their year-on-year emission intensity. Furthermore, countries with higher levels of debt and those heavily reliant on fossil fuel revenues generally have lower ratings post-Paris Agreement, particularly if they are also exposed to climate change risks. Conversely, countries that export commodities that are relevant to the green transition experience improved ratings after 2015.

Our results provide valuable insights for market participants and policymakers, as the use of credit ratings to assess the default probability of sovereign debt is widespread in financial markets and is embedded in various economic and regulatory policies. If current ratings do not systematically reflect risks linked to climate change, there is a substantial likelihood of future repricing of assets exposed to these risks. At the same time, our findings highlight concerns regarding the use of credit ratings for regulatory and macroeconomic policy implementation, as these ratings seem to account for environmental considerations only partially.[25]

[25] Sovereign ratings are integral to most regulations in the financial sector and play a crucial role in monetary policy implementation, as they define the collateral framework and the greening of public sector bond holdings, see for example Schnabel (2023).

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Appendix

Table 9
Summary statistics.

	n	Mean	SD	Min	Max
Average Rating Foreign Currency[a]	2412	12.14	5.24	1	21
S&P Foreign Currency [a]	2145	12.32	5.31	1	21
Moody's Foreign Currency [a]	1250	14.98	5.18	1	21
Fitch Foreign Currency [a]	1782	13.03	5.14	1	21
DBRS Foreign Currency [a]	353	16.43	4.55	1	21
Log GDP per capita ($)	2849	8.62	1.45	4.76	11.79
GDP growth (% change)	2849	3.41	4.39	-35	34.47
Inflation (% change)	2602	6.20	19.63	-8.53	513.91
Debt to GDP ratio (%)	2783	54.28	35.76	0	304.13
Current Account Balance to GDP (%)	2804	-2.49	7.92	-49.47	38.30
External Debt to Export ratio (%)	2523	213.06	178.06	6.26	1,675.18
Temperature Anomalies (Celsius degrees °C)	2698	1.07	0.57	-0.56	3.70
Number of Disasters per Sq. Km	2851	0	0	0	0.01
Change in Disasters (% change)	2852	-0.74	78.11	-100	700
Readiness	2706	0.43	0.14	0.13	0.80
Vulnerability	2684	0.42	0.08	0.25	0.64
Emission Intensity (%)	2726	0.28	0.22	0.02	2.23
Primary Energy Consumption to GDP ratio (%)	2657	1.48	1.08	0.22	12.53
CO2 Reduction Target (% change)	2852	0.04	0.12	0	0.93
Emission Intensity Growth (% growth)	2846	-2.83	9.24	-45.24	104.60
Primary Energy Consumption to GDP Growth (% growth)	2777	-2.78	8.97	-53.60	146.09
FF exports (% of total Export)	2633	13.16	21.43	0	99.66
FF Rents (Oil, Coal and Gas) (% of GDP)	2820	2.91	6.98	0	57.71
FF Rents (Oil and Coal) (% of GDP)	2822	2.52	6.60	0	57.51

[a] See Table 11 for details on rating scale conversion.

Table 10
Selected rating series included in the analysis.

Series	Detailed Rating Description
S&P Issuer Credit Rating (LT,FC)	Forward-looking opinion about an obligor's creditworthiness, defined as its overall financial capacity to pay its financial obligations denominated in foreign currency. This opinion focuses on the obligor's capacity and willingness to meet its financial commitments as they come due. It does not apply to any specific financial obligation, as it does not take into account the nature of and provisions of the obligation, its standing in bankruptcy or liquidation, statutory preferences, or the legality and enforceability of the obligation. In addition, it does not take into account the creditworthiness of the guarantors, insurers, or other forms of credit enhancement on the obligation.
S&P Issuer Credit Rating (LT, LC)	Forward-looking opinion about an obligor's creditworthiness, defined as its overall financial capacity to pay its financial obligations denominated in local currency. This opinion focuses on the obligor's capacity and willingness to meet its financial commitments as they come due. It does not apply to any specific financial obligation, as it does not take into account the nature of and provisions of the obligation, its standing in bankruptcy or liquidation, statutory preferences, or the legality and enforceability of the obligation. In addition, it does not take into account the creditworthiness of the guarantors, insurers, or other forms of credit enhancement on the obligation.
Moody's Issuer Current Long-Term Rating (LT, FC)	Opinion of the ability of entities to honor long-term senior unsecured foreign currency financial obligations and contracts.
Moody's Issuer Current Long-Term Rating (LT, LC)	Opinion of the ability of entities to honor long-term senior unsecured domestic currency financial obligations and contracts.
Fitch Issuer Default Rating (LT, LC)	Opinion on the probability that an issuer would default on its outstanding debt obligations with a time horizon of greater than 12 months for most issuers. In aggregate, IDRs provide an ordinal ranking of issuers based on their relative vulnerability to default, rather than a prediction of a specific percentage likelihood of default.
DBRS Issuer Long-term Rating (LT)	Opinion on the risk of default defined as the risk that an issuer will fail to satisfy its financial obligations in accordance with the terms under which it has been issued. Ratings are based on quantitative and qualitative considerations relevant to the issuer, and the relative ranking of claims.

Table 11
Converting scale (fifth column) for: Standard & Poor's (first column), Moody's (second column), Fitch (third column), and DBRS (fourth column) foreign currency ratings.

S&P	Moody's	Fitch	DBRS	Value
AAA	Aaa	AAA	AAA	21
AA+	Aa1	AA+	AA high	20
AA	Aa2	AA	AA	19
AA-	Aa3	AA-	AA low	18
A+	A1	A+	A high	17
A	A2	A	A	16
A-	A3	A-	A low	15
BBB+	Baa1	BBB+	BBB high	14
BBB	Baa2	BBB	BBB	13
BBB-	Baa3	BBB-	BBB low	12
BB+	Ba1	BB+	BB high	11
BB	Ba2	BB	BB	10
BB-	Ba3	BB-	BB low	9
B+	B1	B+	B high	8
B	B2	B	B	7
B-	B3	B-	B low	6
CCC+	Caa1	CCC+	CCC high	5
CCC	Caa2	CCC	CCC	4
CCC-	Caa3	CCC-	CCC low	3
			CC high	
			CC	
			CC low	2
CC			C high	
C		CC	C	
CI	Ca	C	C low	
R				
SD				1
D	C	D	D	
NR		NR		-

Variable	Description	Source	Transformation	Coverage
	Macroeconomic Variables			
GDP	GDP per capita, constant prices. GDP is expressed in constant international dollars per person. Data are derived by dividing constant price purchasing-power-parity (PPP) GDP by total population. Purchasing power parity in 2017 international dollar.	WEO October 2021, IMF.	Logarithmic transformation	1980-2021
GDP change	GDP, constant prices. Annual percentages of constant price GDP are year-on-year changes; the base year is country-specific. Expenditure-based GDP is total final expenditures at purchasers' prices (including the f.o.b. value of exports of goods and services), less the f.o.b. value of imports of goods and services. [SNA 1993]	WEO October 2021, IMF.		1980-2021
Gross Debt	General government gross debt. Gross debt consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future. This includes debt liabilities in the form of SDRs, currency and deposits, debt securities, loans, insurance, pensions and standardized guarantee schemes, and other accounts payable. Thus, all liabilities in the GFSM 2001 system are debt, except for equity and investment fund shares and financial derivatives and employee stock options. Debt can be valued at current market, nominal, or face values (GFSM 2001, paragraph 7.110). Percent of GDP.	WEO October 2021, IMF.		1980-2021
Inflation	CPI All Items percentage change (yoy).	IFS 2022 M1, IMF.		1980-2020

Variable	Description	Source	Transformation	Coverage
Current Account Balance	Current account balance. Current account is all transactions other than those in financial and capital items. The major classifications are goods and services, income and current transfers. The focus of the BOP is on transactions (between an economy and the rest of the world) in goods, services, and income. Percent of GDP.	WEO October 2021, IMF.		1980-2021
External Debt / Exports [26]	Emerging economies and low income countries: external debt stocks (% of exports of goods, services and primary income). Advanced economies: Gross External Debt Position (All Sectors, All maturities, All instruments, USD) divided by Exports of goods, services and primary income (BoP, current US$)	Emerging economies and low income countries*: IDS, World Bank. Advanced Economies: QEDS and BoPS, World Bank.		QEDS and BoPS: 1980-2020; IDS: 1980-2021
Default indicator	Indicator for previous default. A country is considered to be in default when the balance of debt in default is different from 0. Based on data on total sovereign debt in default.	BoC-BoE Sovereign Default Database 2021, BoC-BoE.		1980-2020

[26] Countries for which we use IDS data. Albania, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Cabo Verde, Cambodia, Cameroon, China, Colombia, Costa Rica, Cote d'Ivoire, Democratic Republic of the Congo, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Grenada, Guatemala, Honduras, India, Indonesia, Islamic Republic of Iran, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao People's Dem. Rep., Lebanon, Lesotho, Madagascar, Malawi, Maldives, Mali, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Nicaragua, Nigeria, North Macedonia, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Senegal, Serbia, South Africa, Sri Lanka, St. Vincent and the Grenadines, Tajikistan, Thailand, Togo, Tunisia, Türkiye, Turkmenistan, Uganda, Ukraine, Uzbekistan, Venezuela, Vietnam, Zambia.

Variable	Description	Source	Transformation	Coverage
Climate Risk Variables				
Temperature Anomalies	Mean surface temperature change by country. Statistics for annual mean temperature anomalies, i.e., temperature change with respect to a baseline climatology, corresponding to the period 1951–1980. Data are based on the publicly available GISTEMP data, the Global Surface Temperature Change data distributed by the National Aeronautics and Space Administration Goddard Institute for Space Studies (NASA-GISS).	FAOSTAT Temperature Change domain		1980-2020
Number of Disasters (floods, droughts, wildfires, storms, heat waves)	A disaster is recorded as such when it has one of the following characteristics: 10 or more people dead, 100 or more people affected, the declaration of a state of emergency, a call for international assistance.	EM-DAT consulted in March 2022. Available at: //www.emdat.be/	Number of disasters in each year. If the disaster end date is in a different year with respect to the start year, the flood is counted in all the years from the start to the end year.	1980-2021
CO2 Emissions		"CO2 and Greenhouse Gas Emissions". Published online at OurWorldInData.org	Divided by GDP (see above)	1980-2020
Primary Energy Consumption	Primary energy consumption, measured in terawatt-hours. Calculated by Our World in Data based on BP Statistical Review of World Energy.	Hannah Ritchie and Max Roser (2021) – Energy. Published in Our World in Data. Online at: ourworldindata.org/energy	Divided by GDP (see above)	1980-2020

Variable	Description	Source	Transformation	Coverage
CO2 Reduction Target	Percentage difference between IMF estimates for CO2 emissions in 2050 in the "business as usual"and "target achievement" scenarios	National Greenhouse Gas Emissions Inventories and Implied National Mitigation (Nationally Determined Contributions) Targets, available at https://climatedata.imf.org/datasets/72e94bc71f4441d29710a9bea4d35f1d0/about	Interacted with dummy which takes value of 1 for years after the ratification of the Paris Agreement (constructed based on the data contained in https://www.iges.or.jp/en/pub/iges-indc-ndc-database/en)	
Fossil Fuel exports	Fossil Fuel Export as % of merchandise export.	World Bank, available at https://data.worldbank.org/indicator/TX.VAL.FUEL.ZS.UN consulted in April 2023.		
Fossil Fuel rents (Oil, Coal, and Gas)	Values for oil, coal, and gas rents as a % of GDP.	World Bank, available at: https://data.worldbank.org/indicator/NY.GDP.PETR.RT.ZS, https://data.worldbank.org/indicator/NY.GDP.COAL.RT.ZS,https://data.worldbank.org/indicator/NY.GDP.NGAS.RT.ZS, consulted in April 2023.	Indicators computed summing rents for fossil fuels including and excluding gas.	

Variable	Description	Source	Transformation	Coverage
Net Exports of Copper, Graphite, Lithium, Cobalt, Rare Earths, Nickel and Manganese.	Annual values in current US dollars for net exports of copper (ores and concentrates), artificial graphite, lithium carbonates, cobalt (ores and concentrates) earth metals: scandium and yttrium (whether or not intermixed or inter-alloyed), Nickel (ore and concentrates), Manganese (ores and concentrates) including manganiferous iron ores and concentrates with a manganese content of 20% or more, calculated on the dry weight.	World Integrated Trade Solutions (WITS) World Bank, available at: https://wits.worldbank.org/trade/country-byhs6product.aspx?lang=en.	Share of transition critical material exports over total export is computed. Several alternative measures of high export of transition-critical materials are derived based on this percentage.	1998-2022
Physical Risk Exposure	Indicator of physical risk exposure derived from EIB scores.	EIB - Internal calculations		2020
Transition Risk Exposure	Indicator of transition risk exposure derived from EIB scores.	EIB - Internal calculations		2020

Table 12
Macroeconomic and climate variables included in the analysis, data descriptions, sources, transformations, and coverage.

Table 13
Results for panel regression computed on 124 countries over the time window from 1999 to 2021. The model follows Cantor and Packer (1996).

	Rating
	(1)
Log GDP t-1	2.014***
	(0.371)
GDP Growth t-1	0.0345**
	(0.0157)
Inflation t-1	-0.0185***
	(0.00594)
Debt to GDP ratio t-1	-0.0336***
	(0.00887)
Current Account Balance to GDP ratio t-1	-0.0114
	(0.0101)
External Debt to Export ratio t-1	-0.00197**
	(0.000773)
Default	-0.799*
	(0.428)
Economy	5.854***
	(1.223)
Constant	-4.328
	(2.898)
Observations	2,013
R-squared	0.956
Country FE	YES
Year FE	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 14
ESG factors in standard sovereign ratings from S&P, Fitch, Moody's, and DBRS.

	Standard & Poor's	Moody's	Fitch	DBRS Morningstar
Materiality	ESG incorporated through the application of sector-specific criteria when these are, or may be, relevant and material to our credit ratings.	ESG incorporated when those have a material impact on credit quality.	ESG factors included when relevant and material for creditworthiness.	ESG factors included when those have discernible impact(s) on an issuer's creditworthiness.
Horizon	If there is high uncertainty about when and how a credit factor can change, that credit factor is monitored but not necessarily included. As the timing and likelihood of these events become clearer those risks may be included into our view of creditworthiness.	ESG issues can result in a wide range of potential credit outcomes for affected issuers. In some cases, the expected impact of ESG risks may extend beyond the period projected in the scorecard metrics, or there is insufficient information to project the impact with reasonable precision.	Many consequences of climate change are not expected to occur for several decades, while current ratings decisions typically place more weight on current developments.	NA

Environmental Factors	1) Climate transition risk factors,(climate policy; legal, technology, and market changes to address mitigation and adaptation requirements related to climate change) 2) Physical risk factors (event-driven or longer-term shifts in climate patterns) 3) Natural capital factors (stock of natural resources) 4) Waste and pollution factors (waste products, water pollutants, and air emissions other than greenhouse gas emissions) 5) Other environmental factors.	(i) carbon transition; (ii) physical climate risks; (iii) water management; (iv) waste and pollution and (v) natural capital (see Tab 2).	1) 'Physical' risks (potential impact of higher temperatures, increasing drought, rising sea levels and more extreme weather events and incidences of natural disasters.) 2) 'Transition' risks (exposure to potentially 'stranded assets' - such as fossil fuel resources - driven by changes in global policies, technology or consumer preferences, and the costs of transitioning to a lower-carbon economy.) 3) Adaption capacities of sovereigns (deploying resources and know-how to limit physical risks or diversifying economies to limit transition risks.)	1) Emissions, Effluents, and Waste 2) Carbon and Greenhouse Gas (GHG) Costs 3) Resource and Energy Management 4) Land Impact and Biodiversity 5) Climate and Weather Risks

Quantitative or Qualitative	Quantitative: when it is possible to include it in the financial forecast (when forecasting other related factors). Qualitative: if a ESG factor becomes more material after the rating horizon. See tab 2	Quantitative: in case of sufficient visibility, ESG considerations may be incorporated into projections or scorecard-indicated outcomes evaluated in a variety of scenarios. Qualitative: in case the expected impact of ESG risks extends beyond the period that meaningfully projected ore there is insufficient information to project the impact with reasonable precision.Also, Issuer Profile Scores (IPSs) indicating opinion on ESG risk exposure are produced and used as inputs to credit ratings.	Quantitative: if ESG variables have some correlation with classic variables included in the rating methodology, there are reflected in the rating. Quantitative: Qualitative Overlay for forward-looking rating adjustments when climate change risk is sufficiently relevant and material to credit worthiness.	Impacts assessed qualitatively.

Sources: Standard & Poor's (2021), Moody's Investor Service (2021), Fitch Ratings (2022), DBRS Morningstar (2021).

Table 15
Results for panel regressions in Equation 2 from 1999 to 2021. Cantor and Packer (1996) augmented with physical risk variables. Results for EU and non-EU countries.

	Rating									
	EU	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Temperature Anomalies t-1	-0.548***	-0.110								
	(0.188)	(0.0844)								
Percentage Change in Disasters t-1			0.000438	-0.000615**						
			(0.000630)	(0.000259)						
Number of Disasters per Sq. Km t-1					-461.5	-253.3				
					(746.8)	(189.2)				
Vulnerability							37.17	-10.63		
							(22.44)	(11.03)		
Readiness									17.44**	7.639***
									(7.351)	(1.993)
Observations	502	1,498	502	1,511	502	1,511	477	1,405	477	1,411
R-squared	0.929	0.956	0.927	0.956	0.927	0.956	0.930	0.955	0.935	0.958
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16
Results for panel regressions in Equation 2 from 1999 to 2021. Cantor and Packer (1996) augmented with transition risk variables. Results for EU and non-EU countries.

	Rating									
	EU	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**	**EU**	**non-EU**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Emission Intensity t-1	0.895	-0.247								
	(2.556)	(0.571)								
Primary Energy Consumption to GDP ratio t-1			0.195	0.149						
			(0.946)	(0.250)						
CO2 ReductionTarget					-0.965	0.585				
					(1.282)	(0.678)				
Emission Intensity Growth t-1							0.00886	0.00124		
							(0.00854)	(0.00333)		
Primary Energy Consumption to GDP ratio Growth t-1									0.00876	-0.00154
									(0.00950)	(0.00446)
Observations	502	1,511	502	1,467	502	1,511	502	1,511	502	1,467
R-squared	0.927	0.955	0.927	0.957	0.927	0.956	0.927	0.955	0.927	0.957
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17

Results for panel regressions in Equation 2 from 1999 to 2021. Cantor and Packer (1996) augmented with physical risk variables. Results for advanced (AE) and emerging (EE) economies.

	Rating									
	AE	**EE**	**AE**	**EE**	**AE**	**EE**	**AE**	**EE**	**AE**	**EE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Temperature Anomalies t-1	-0.447**	-0.0764								
	(0.197)	(0.0770)								
Percentage Change in Disasters t-1			-0.000678	-0.000461*						
			(0.000499)	(0.000258)						
Number of Disasters per Sq. Km t-1					-26.30	-278.6				
					(138.1)	(248.5)				
Vulnerability							29.36	-13.25		
							(31.85)	(12.26)		
Readiness									18.21**	6.982***
									(7.338)	(1.737)
Observations	631	1,369	631	1,382	631	1,382	581	1,301	581	1,307
R-squared	0.887	0.901	0.884	0.900	0.884	0.900	0.888	0.901	0.894	0.906
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18

Results for panel regressions in Equation 2 from 1999 to 2021. Cantor and Packer (1996) augmented with transition risk variables. Results for advanced (AE) and emerging (EE) economies.

	Rating									
	AE	**EE**	**AE**	**EE**	**AE**	**EE**	**AE**	**EE**	**AE**	**EE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Emission Intensity t-1	-2.773	-0.0470								
	(2.713)	(0.548)								
Primary Energy Consumption to GDP ratio t-1			-1.087*	0.312						
			(0.566)	(0.230)						
CO2 ReductionTarget					0.509	0.315				
					(0.879)	(0.615)				
Emission Intensity Growth t-1							0.0170	0.000778		
							(0.0108)	(0.00345)		
Primary Energy Consumption to GDP ratio Growth t-1									0.00882	-0.00231
									(0.0115)	(0.00454)
Observations	631	1,382	631	1,338	631	1,382	631	1,382	631	1,338
R-squared	0.885	0.900	0.886	0.902	0.884	0.900	0.885	0.900	0.884	0.902
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19
Weighted panel regressions for 124 countries from 1999 to 2021. Cantor and Packer (1996) augmented with physical risk variables. Weighted by GDP in US dollars.

	Rating				
	(1)	(2)	(3)	(4)	(5)
Temperature Anomalies t-1	-0.287***				
	(0.0949)				
Percentage Change in Disasters t-1		-0.000596*			
		(0.000335)			
Number of Disasters per Sq. Km t-1			-284.0		
			(222.2)		
Vulnerability				-17.83	
				(19.87)	
Readiness					2.655
					(2.341)
Observations	1,999	2,012	2,012	1,882	1,888
R-squared	0.958	0.958	0.958	0.958	0.959
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20
Weighted panel regressions for 124 countries from 1999 to 2021. Cantor and Packer (1996) augmented with transition risk variables. Weighted by GDP in US dollars.

	Rating				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity t-1	-0.305				
	(2.119)				
Primary Energy Consumption to GDP ratio t-1		-0.369			
		(0.557)			
CO2 ReductionTarget			1.860***		
			(0.589)		
Emission Intensity Growth t-1				0.00866	
				(0.00668)	
Primary Energy Consumption to GDP ratio Growth t-1					0.0146
					(0.0104)
Observations	2,012	1,968	2,012	2,012	1,968
R-squared	0.958	0.958	0.959	0.958	0.958
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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The views expressed in this paper are the responsibility of the authors and should not be interpreted as reflecting the views of, or implying any responsibility for, the European Central Bank, the Eurosystem, the International Monetary Fund, and the Bank of England.

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