Climate Risks' Impact on Debt-to-GDP and Implications on Sovereign Default Probability

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Abstract

The debt-to-GDP ratio has been recognized as an important factor for sovereign default risk, demonstrated through instrument values like bond yield and credit default spread. In a climate risk perspective, debt-to-GDP ratio will be impacted by the severity of environmental adversity and the effort from governments to mitigate the uncertainties. Under different climate change scenarios corresponding to respective global warming levels, economies will incur GDP loss from physical risk, debt increase from transition risk, or a combination effect of both.

We develop two models to incorporate climate risk in the simulation of debt-to-GDP ratio of 18 countries with different economic and geographical characteristics up to 2050, using penalties induced by climate change scenarios and other sustainability-related factors. The models use the debt-to-GDP outlook to evaluate the potential year of sovereign default for a scenario and the sovereign default probability for a specific year. The models enable cross-sectional analysis, which shows economic resilience of developed countries relative to emerging countries in the face of damage implied by climate risk.

Keywords: climate change scenarios, climate transition risk, climate physical risk, sovereign bond, default probability, debt-to-GDP

We acknowledge academic and data support from Western Asset Management. We thank Roberto Apelfeld, Tania Labastida, Paulo Caricati, Marjan Zahedi, Brishni Mukhopadhyay, and Bonnie Wongtrakool for the guidance and comments on the logic behind the calibration and adjustment of our models throughout the scope of this project.

Contents

1. Introduction

Due to the recent rise in attention to global sustainability issues, the impact of climate risk, a major component of environmental concerns, has received increased academic scrutiny in an attempt to uncover its ties to financial stability for investors and institutions around the globe. Specifically, how climate risk will impact the performance and risk characteristics of securities has become a factor of decision-making for investors and managers. From the mid-2010s, studies have emerged with theories to incorporate risks induced by climate change, in notable forms of 1) physical risk, the uncertainty of the damage extreme phenomenon from changing climate patterns will induce to security issuer, 2) transition risk, the costs faced by security issuer to carry out efforts to mitigate climate risk, such as carbon emission reduction.

This project focused on one specific class of financial instruments – sovereign bonds. Past studies have shown that climate change is associated with increases in the sovereign CDS premiums (Diarra et al., 2022), and various sustainability-related factors, such as emissions and renewable energy development, have connections to the borrowing cost of national debt (Collender et al., 2022). Furthermore, such impact has been indicated to correlate with climate scenarios on temperature rise, defined by international organizations like Intergovernmental Panel on Climate Change (IPCC). Because the issuer of sovereign securities are typically the governments of economies, which are also the key players for national sustainability progress, we tried to determine a link between the forthcoming climate risk and the evolution of macroeconomic characteristics. The relationship would then provide us with a bridge to sovereign credit risks demonstrated through bonds and credit default swaps (CDS). National characteristics, such as geographical location, economic advancement, and debt burden relative to national income, could all be factors of cross-sectional sovereign credit risk. As such, given a climate scenario, a country's sovereign risk may examine specific behavior that could potentially result in default, where we defined as the inability to service national debt through wealth. The risk was measured through a key indicator: debt-to GDP (DGR) ratio. To put simply, in face of climate risk, how countries incur changes in debt issuance for transition risk and in GDP loss related to physical risk would lead to adjustment to its credit risk.

In the following sections, we will start with a detailed review of relevant literature contributing to the inspiration and logic behind our methodologies for research. Then, we describe the data we collected across data providers and international institutions for a basket of 18 countries with varying national characteristics. The section following will lay out our methodologies to evaluate sovereign default risk, taking two major approaches: 1) default probability simulation, which, for a given future year, measures the probability a country might default under its evolution of debt and GDP for a given climate scenario, and 2) time-series of default, which examine the timing of each country default using simulation and factoring other relevant variables. We will report results for both approaches and examine cross-sectional output for the 18 countries with different economic developments and locational features. Finally, we will discuss the implications of the conclusions in our studies and extend directional suggestions for further research in this area.

2. Literature Review

The combined challenges of climate change and their economic repercussions have brought about an era of urgency and complexity. As the whole world deals with the problems of a warming planet, we're starting to see that climate change doesn't just affect the environment. It also has a big impact on how we run our societies and economies. This literature review delves into the critical intersection of climate scenarios, economic consequences, and their implications for sovereign states, with a particular focus on the dynamics of sovereign debt and Gross Domestic Product (GDP).

To understand the evolution of climate change, extensive research has focused on predicting future temperature trends. This effort has resulted in the development of various potential trajectories or scenarios for temperature increase. Among these, the most prevalent scenarios utilized in climate studies are the Representative Concentration Pathway (RCP) scenarios introduced by the Intergovernmental Panel on Climate Change (IPCC). RCPs are typically categorized into four main scenarios, from RCP 2.6—a low emissions, climate mitigation pathway, striving to cap global temperature increase significantly below 2°C, to RCP 8.5—a high emissions, business-as-usual pathway, projecting 4°C or more of global warming (IPCC, 2014). Under these different scenarios, climate change poses two types of risks—physical risks, which involve the direct and immediate impacts on the environment and society, and transition risks, which stem from the process of transitioning to a low-carbon economy and adapting to new climate policies and technologies.

Physical risks encompass a range of factors, including harm to property, interruptions in trade caused by climate-related events like storms, floods, and droughts, and decreased productivity resulting from increasing average temperatures, among other factors (Swiss Re Institute, 2021). Sudden and intense events like hurricanes or floods are referred to as acute risks, and ongoing, gradual changes such as temperature increases, and rising sea levels are referred to as chronic risks (FTSE Russell, 2021).

The process of shifting toward a more environmentally friendly economy poses transition risks. This involves altering resource allocation, adopting new technologies, and implementing regulatory changes. These shifts necessitate a reevaluation of asset values, create "stranded" assets like fossil fuel resources or coal reserves, and introduce the potential for systemic devaluation risks within the global financial sector (Swiss Re Institute, 2021).

In studying climate change, damage functions are commonly used tools that connect rising temperatures to reductions in GDP. One method for estimating the economic impact of climate change involves using an econometric regression model to establish a quadratic relationship between the growth in GDP per capita and the average annual temperature. The objective is to determine the 'optimal temperature range' where productivity is maximized, both below and above which productivity declines. This approach takes into consideration the variations in the relationship between temperature and productivity growth within individual countries and across different countries. Some of the factors considered in this analysis include the historical average annual temperature and the increase in the average annual temperature of various countries (FTSE Russell, 2021).

Another way of studying the impact of physical risks on modern economies, is to employ a macroeconomic model (Moody's Analytics, 2019, as cited in Swiss Re Institute, 2021) that incorporates the responsiveness of productivity and various other factors to increasing temperatures in the context of 6 specified climate change "impact channels," (Roson and Sartori, 2016, as cited in Swiss Re Institute, 2021) which include areas like agriculture and heat-related stress. Apart from utilizing these six impact pathways, additional unexamined channels, which are the ones that haven't been measured in prior studies, can also be integrated. These omitted channels encompass a range of factors, including but not limited to climate-induced migration, and impacts on biodiversity. Most of these factors tend to lead to negative economic consequences. Furthermore, it's possible to factor in multiplicative factors (x5 and x10) to represent varying degrees of potential outcomes stemming from known and unknown factors when studying the impact of climate change on GDP (Swiss Re Institute, 2021).

To reduce the physical threats posed by climate change, all member nations of the United Nations reached a consensus during the COP21 conference in Paris to cap global warming well below 2°C. Achieving this objective necessitates a substantial reduction in greenhouse gas (GHG) emissions, ultimately reaching a state of net zero emissions by this century's latter half. Such a change would entail a major reshaping of the global economic system, with particular significance on the countries heavily reliant on fossil fuels and related technologies. The way this transition occurs can be broadly categorized as orderly or disorderly, giving rise to what is termed a "transition risk." Deliberately delaying mitigation measures would ultimately result in the need for costly emergency technologies, leading to a disorderly transition (FTSE Russell, 2021).

The global carbon budget remaining to restrict the increase in global temperature to 2°C with respect to pre-industrial times is estimated at 1500 GtCO2eq for a probability of 50%, or 1170 GtCO2eq for a probability of 67%. Aligned with the 2°C target, these national carbon budgets are used up annually by the emission of GHGs. Differences in emissions among countries arise from variations in factors such as GDP per capita. The total abatement costs for reducing emissions in a country, in monetary terms, reflect the number of emissions that still need to be reduced once a country's carbon budget has been exhausted. These costs would have an impact on the nation's GDP. Also, shifting a substantial portion of a country's resources away from productive activities in a short timeframe is likely to require substantial financial support, potentially affecting the sustainability of national debt (FTSE Russell, 2021).

According to recent studies, there are strong links between climate risks and sovereign assets. Models have been developed to quantify how changes in climate impact sovereign-bond returns. Under the RCP 8.5 scenario, the damages incurred would raise nations' DGR. This is due to a decline in government revenue caused by losses in infrastructure, employment, etc. which, in turn, diminish the taxable income base. In the disorderly transition scenario, it is assumed that the government fully covers the costs of emission reduction. This is because the investment in alternative technologies primarily becomes a matter of public policy. Consequently, this scenario would contribute to the budget deficit and lead to an increase in the DGR (FTSE Russell 2021). Several measures of a country's effort in mitigating climate risk have also had their significance as determinants of sovereign yields and spreads studied. Carbon dioxide emissions and natural resource rents as % GDP have been found to have positive correlations to sovereign bond yields and spreads for both developed and undeveloped countries, with the effect more observable for advanced markets. On the other hand, renewable energy consumption has been shown to have a negative correlation (Collender et al., 2022).

The likelihood of a sovereign default can then be assessed by employing the concept of a "default threshold". This threshold represents the maximum DGR a government can repay without experiencing a default (Collard et al., 2015, 2016, as cited in FTSE Russell, 2021). In the model used by FTSE Russell (2021), the difference between the current DGR and the default threshold signifies the remaining fiscal capacity in terms of a percentage of GDP before a default occurs. When a government's DGR reaches or surpasses this default threshold, it is anticipated to default. The fiscal capacity that is remaining, that is, the gap between the default threshold and the current DGR, is defined as the "critical minimum growth rate". Hence, we can establish the concept of default probability, which represents the probability of the GDP growth rate falling to the critical minimum level necessary to avert default. Now, to link default probability with sovereign bond returns, a default risk premium is determined, which in turn determines the sovereign interest rate.

The risk premium related to default is directly linked to the likelihood of default, which means that an escalation in the probability of default due to climate change will result in a corresponding rise in the sovereign interest rate. An uptick in yield will consequently diminish the returns on bonds. Therefore, the influence of climate change on the returns from sovereign bonds is highlighted. Climate-related damage could alter the debt dynamics, potentially raising the likelihood of default and causing an increase in the yield on a nation's bonds, thus resulting in reduced returns.

3. Data

The project primarily utilized three sources to satisfy the scope and length of data we required to establish meaningful quantitative results for sovereign default risk: 1) Refinitiv Eikon, which provided country-specific time series data on sovereign securities and economic indicators, 2) guiding literature (Swiss Re Institute, 2021), which gave outlook for countries under climate stress and economic penalties for climate scenarios, and 3) World Bank, which supplemented several factors that were potentially linked to DGR.

We focused on data from the empirical period between 2012 and 2022, where both sovereign instrument data, economic data, and sustainability data were becoming better documented for governments around the world, and the data would be used for default risk examination over the horizon from 2024 to 2050.

3.1 Universe of Economies

Given a wider universe of global economies potentially available in data sources, we refined the distributions of inputs in the model for implementation of cross-sectional analysis. We began with a basket of 52 economies and shrank down the list by completion of data. Given the restricted time frame between 2012-2022, the quantity and quality of data accessible was optimal. Through data selection and aggregation, we determined 18 economies with data series sufficient for model input. We also documented several categorical characteristics in preparation for cross-sectional analysis later. The list of economies with the country's characteristic variables is displayed in the table below.

Economy	Abbreviation	Latitude	Hemisphere	Developed?
Canada	CA	60-90	N	No
Chile	CL	30-45	S	No
China	CN	30-45	N	No
Denmark	DK	45-60	N	Yes
France	FR	45-60	N	Yes
Germany	DE	45-60	N	Yes
India	IN	0-30	N	No
Italy	IT	30-45	N	Yes
Japan	JP	30-45	N	Yes
Netherlands	NL	45-60	N	Yes
Peru	PE	0-30	S	No
Portugal	PT	30-45	N	Yes
Republic of Ireland	IE	45-60	N	Yes
Slovakia	SK	45-60	N	Yes
South Korea	KR	30-45	N	Yes
Spain	ES	30-45	N	Yes
United Kingdom	GB	45-60	N	Yes
United States	US	30-45	N	Yes

3.2 Refinitiv Eikon

Refinitiv Eikon as the primary source of data. We started by exploring several economies with presumed traceable time series data in sovereign instruments, selecting United States, Germany, China, and India for initial model development and calibration. These countries have been previously studied for potential loss of national wealth under various climate change scenarios (FTSE Russell, 2021), which allowed us to incorporate reasonable estimates of scenario-based penalties into our model. From there, we identified a list of input variables necessary for us to build the model, separated into two categories: economic indicators and sovereign fixed income data. An overview of the variables, including description and data frequency, is displayed in the following table.

Variable	Description	Category	Data Frequency
GDP	Gross domestic product corresponding to fiscal year	Economic Indicator	Annual
Debt-to-GDP	General government gross debt, % GDP	Economic Indicator	Annual
Deficit	Period central government deficit/surplus	Economic Indicator	Monthly
CPI	Period-to-period CPI % change	Economic Indicator	Monthly
CDS	Credit default swap value	Instrument Data	Daily
GOV1Y	Bond yield for 1-year treasury security	Instrument Data	Daily
GOV2Y	Bond yield for 2-year treasury security	Instrument Data	Daily
GOV5Y	Bond yield for 5-year treasury security	Instrument Data	Daily
GOV10Y	Bond yield for 10-year treasury security	Instrument Data	Daily
GOV30Y	Bond yield for 30-year treasury security	Instrument Data	Daily
CDS	1-year sovereign CDS spread value	Instrument Data	Daily
CDS30	30-year sovereign CDS spread value	Instrument Data	Daily

3.3 Swiss Re Institute, 2021

From publications on economic impact from climate change, we fetched country-specific data points regarding annual GDP % loss in each of the four climate scenarios – below 2°C increase, 2°C increase, 2.6°C increase, and 3.2°C increase – relative to an ideal circumstance with no climate change (0°C increase). The magnitude of GDP loss could be further stressed with a severity multiplier at x5 or x10, representing conservative estimates to unknown externalities that may come with climate risk (Swiss Re Institute, 2021). We would use these loss estimates as linearly extrapolated penalties when simulating DGR in the future. Below are the 4 temperature increase scenarios with their respective GDP loss projection for each country.

Country	1.5°	2°	2.6°	3.2°
Canada	-1.40%	-3.40%	-3.50%	-4.60%
Chile	-4.10%	-9.90%	-10.80%	-14.10%
China	-3.30%	-7.70%	-9.20%	-12.10%
Denmark	-0.30%	-1.40%	1.00%	-1.60%
France	-1.70%	-4.90%	-4.90%	-6.50%
Germany	-1.60%	-4.00%	-4.00%	-5.40%
India	-3.00%	-8.90%	-13.90%	-18.00%
Italy	-2.30%	-5.60%	-5.90%	-7.70%
Japan	-1.60%	-4.20%	-4.50%	-6.00%
Netherlands	-0.80%	-2.40%	-2.30%	-3.20%
Peru	-2.50%	-5.10%	-5.70%	-6.90%
Portugal	-1.30%	-3.20%	-3.30%	-4.30%
Republic of Ireland	-1.10%	-3.20%	-3.10%	-4.20%
Slovakia	-1.30%	-4.00%	-3.80%	-5.20%
South Korea	-3.00%	-4.20%	-4.70%	-6.30%
Spain	-1.30%	-3.60%	-3.80%	-4.90%
United Kingdom	-1.10%	-3.20%	-3.10%	-4.20%
United States	-1.70%	-3.60%	-3.90%	-5.00%

3.4 World Bank

Guided by past literature (Collender et al., 2022), we also accessed annual time series data from World Bank for all countries regarding the three factors relating to environmental transition effort: 1) CO2 emissions (metric tons per capita), 2) total natural resources rents (% of GDP), and 3) renewable energy consumption (% of total final energy consumption). The data in this front was less recent, often going as late as 2020 or 2021. We assumed autocorrelation within these factors to better simulate factor value evolution up to 2050, which should correspond to realistic country behavior to a reasonable extent.

4. Methodology

In this paper, we aim to model scenarios of countries' defaulting on their debt contingent on climate stresses. The intricate relationship between a nation's debt and its Gross Domestic

Product (GDP) has long been a focal point of economic research. This DGR, a pivotal metric, offers insights into a country's fiscal health and its ability to manage and service its debt. DGR is used in many papers such as FTSE Russel, 2021 and Collard, 2015, as the proxy of a country's economic health. In our model, we delve into a comprehensive modeling exercise, drawing inspiration from the (FTSE Russell, 2021) paper but introducing nuanced modifications to cater to our specific objectives. We defined a DGR threshold inferred by credit default swap (CDS) spread. We will try to find how climate stresses in debt and GDP dynamics move the DGR paths. We have two methods that we want to use to predict climate-induced default events using DGR, namely 4.1 Default Probability Simulation, and 4.2 Time Series of Default. We then mapped these methods to 18 countries with 4 different climate scenarios.

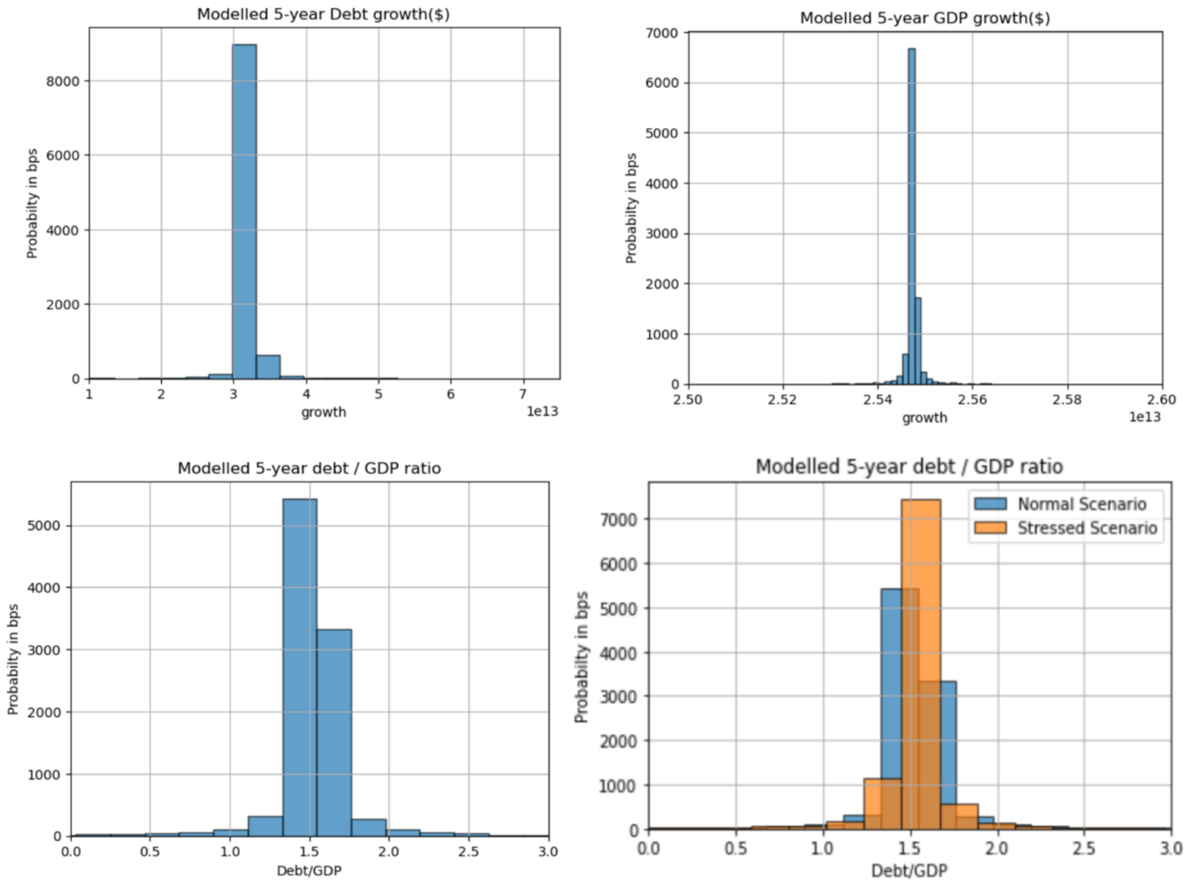
4.1 Credit Default Swap (CDS)

We take the 5-year CDS on Sovereign bonds for each of the 18 countries, assuming a 40% recovery rate, as a proxy for the probability of default in 5 years. Then, jointly with the GDP and debt paths simulation model stated in the 4.2 section, 1) Generate the potential 5-year DGR paths 2) Find the distribution of the DGR 3) Set the defaulting DGR threshold flat at the bottom PD percentile of the 5-year CDS implied default probability. Effectively, we are using the 5-year CDS implied default probability and the 5-year Debt to GDP distribution to find the optimal cutoff for the defaulting DGR threshold in our model. We determined the 5-year CDS as the proxy since shorter horizon CDS tend to be a lot more volatile, and longer horizons reflect less of the current market views of sovereign creditability. Bootstrapping the CDS curve would also be a great solution, however, it would create a dynamic DGR threshold, adding complexity to readability of climate spread dynamics.

4.2 Default Probability Simulation

We take historical data of each country and use these variables: GDP (Nominal), Inflation, DGR. Central to our modeling approach was the selection of the Cauchy distribution to represent GDP growth. Williams et al (2017) have researched in their paper that GDP is more fitting towards a Cauchy distribution and is certainly not following normal distribution properties. The Cauchy distribution, with its unique ability to capture the tails of data distributions, offers a more encompassing representation of economic data, especially when compared to the conventional normal distribution.

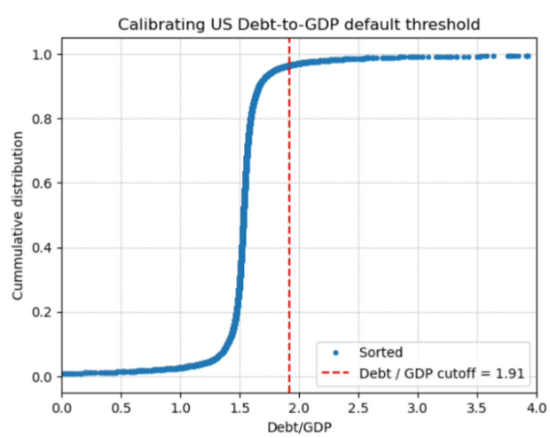
With the calculation of percentage changes in GDP, we simulate the Cauchy distribution and capture the medium and scale of it. Transitioning from GDP growth, our attention shifted to the dynamics of debt. We computed the percentage change in debt, ensuring that this data too was represented using the Cauchy distribution. This consistent application of the Cauchy distribution ensured methodological coherence across our analyses and can be calculated further. By fitting our 10,000 set of GDP growth and debt dynamics to their respective Cauchy distributions, we were able to derive a new Cauchy distribution that captures the DGR. This merged distribution served as the backbone for our subsequent analyses. From these simulations, we are able to model the stressed scenarios. For this section we display (one the bottom right) the simulation of the stressed scenario using 1% deduction from GDP growth just to display that adding stress to GDP growth will cause the simulation output to shift rightwards. In the Result section, we display our result of the same 4 scenarios using the same increments mentioned in the first method.



Two critical assumptions underpinned our modeling exercise. First, we assumed no correlation between individual years, allowing for independent sampling. Second, we propose no correlation between GDP growth and debt dynamics. We thereby can run the simulation 5 times to capture 5 years by these assumptions. While these assumptions facilitated our current modeling, we acknowledge the potential need for adjustments in future iterations.

Drawing 10,000 random samples from our merged Cauchy distribution, we simulate the distribution. These samples were replicated five times, offering a projection of potential outcomes over a half-decade horizon. A feature of the model of our code is its flexibility; the year parameter can be adjusted, allowing for projections tailored to specific years like 2030 or 2050.

The Cumulative Distribution Function (CDF) of our DGR values was instrumental in determining the default threshold. Directly interchanging the histogram of our distribution, we get the CDF, a more holistic perspective of the picture, allowing us to understand it better. For the example below, the horizontal dashed line on the CDF, representing the 96.4th percentile, demarcates the worst 3.56% scenarios. The probability of default (3.56%) is calculated based on the annual CDS spread, which is quantified at 44.83 basis points (bps). By incorporating a recovery rate of 40%, as stipulated by the (FTSE Russell, 2021) paper, we can derive the implied five-year probability of default of 3.56%. With the formula, we can also get the probability of default in any given year. On the other hand, the vertical dashed lines corresponding to this threshold, 1.91, which is the DGR cutoff that determines the tangible metric to measure the possibility of future defaults. With the structure of the model constructed, we can move on to incorporate factors like climate risk penalties which we will discuss later in the paper.



4.2.a. Determine the Penalty

For our first methodology, the penalties for climate change risks are intricately tailored to each country, focusing on the distinct impacts of physical and transition risks. This approach contrasts with the FTSE Russell paper's methodology, which employs a more generalized model to assess the economic impacts on sovereign debt dynamics. In the FTSE Russell framework, the "hot house world" scenario addresses the damages from physical risks by attributing them to reductions in fiscal revenues, which, in turn, lowers the tax base and increases the debt-to-GDP ratio. In the "disorderly transition" scenario, government expenditures rise due to the assumption that abatement costs, crucial for investment in backstop technologies, are fully funded by the government, again increasing the debt-to-GDP ratio.

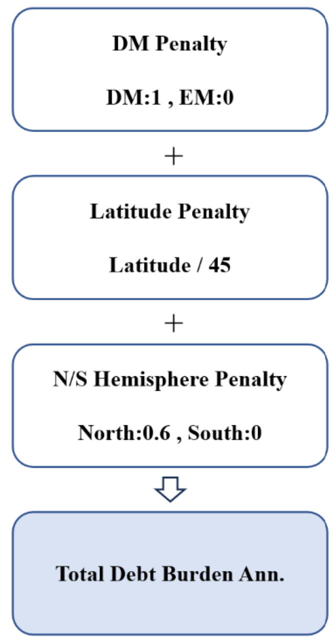
The FTSE Russell paper also employs a default probability model based on the notion of a default threshold, representing the maximum debt-to-GDP ratio a government can reimburse without defaulting. The difference between this threshold and the current debt-to-GDP ratio indicates the remaining "fiscal space" before default. The model posits that the evolution of the debt-to-GDP ratio depends solely on the GDP growth rate, and the probability of exceeding the default threshold is linked to the decline in GDP growth.

In contrast, our methodology offers a more nuanced and country-specific assessment. We recognize the different impacts of climate risks on various economies, making it potentially more accurate for individual countries' economic contexts. We apply specific penalties for each country based on the GDP decrease due to physical risks and an increase in debt for transition risks. Notably, we also include a 1.5x buffer for developed countries on the debt penalty, acknowledging their higher baseline debt levels and substantial sustainability transitions.

This tailored approach allows for a more detailed and context-specific analysis, potentially providing a more accurate forecasting and planning tool. By focusing on the particularities of each country's situation, our model offers insights that are more relevant and actionable for individual economies, enhancing the predictive power and relevance of the model in understanding sovereign risk in the context of climate change.

On the debt side, we add transitional risk penalties with a scoring system using geographic and economic development data, giving penalty weights to different geographic and economic traits. DM markets tend to be more proactive in climate mitigation, thus receives a penalty; Higher the latitudes countries will suffer from more temperature increases as shown in (FTSE 2022); Southern hemisphere countries suffer less from temperature increases due to the conditioning effect of neighboring seas and less clumped up land. The total transitional risk penalty we apply in our model is shown in the graph below.

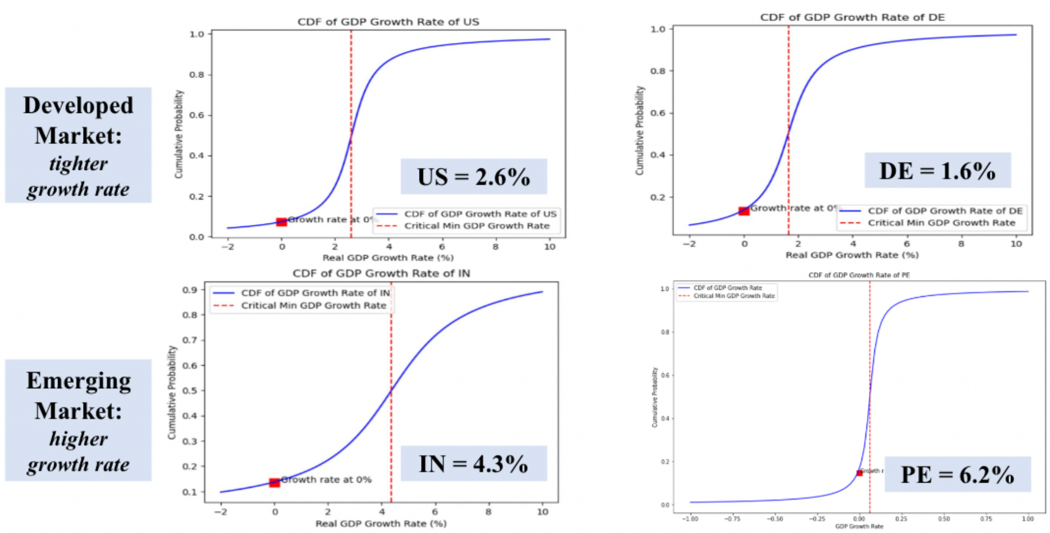
	latitude	hemisphere	Developed	Transitional risk
Canada	60	1	1	2.94
Chile	30	0	0	0.66
China	30	1	0	1.26
Denmark	30	1	1	2.26
France	30	1	1	2.26
Germany	30	1	1	2.26
India	0	1	0	0.60
Italy	30	1	1	**2.26**
Japan	30	1	1	**2.26**
Netherlands	30	1	1	**2.26**
Peru	0	0	0	0.00
Portugal	30	1	1	**2.26**
Ireland	30	1	1	**2.26**
Slovakia	30	1	1	**2.26**
South Korea	30	1	1	**2.26**
Spain	30	1	1	**2.26**
UK	30	1	1	**2.26**
US	30	1	1	**2.26**



4.3 Time Series of Default

The first method is focused on finding how the implied probability of default is moving as we induce climate stresses. Meanwhile, this method is focused on finding the year where the path is crossing the default threshold for each scenario. We apply two thresholds and two methods in finding time series of default. The first threshold is the fiscal threshold is what Collard (2015) referred to as Maximum Sustainable Debt. The distance from the DGR to fiscal threshold is called *fiscal space*. To determine fiscal threshold, Collard (2015) uses a formula that includes primary surplus (deficit), which refers to current government spending less current income from taxes, and excludes interest paid on government debt, based on MERK Investment LLC definition. If the number is positive (negative) we can call this primary surplus (deficit).

In our approach, we defined fiscal space as *critical minimum growth rate*, like FTSE Russel (2021). We took historical GDP growth rate of 10 years, sort them, and fit them into Cauchy distribution. We then took the median as the critical minimum growth rate. The reason being is that we project that we believe that historical real GDP growth rate is a good proxy for country's productivity expectation, thus can keep an economic cushion above its current debt. For historical fiscal threshold, we take the minimum of actual real growth rate at time *t* and critical minimum GDP growth rate to determine the fiscal threshold. For future fiscal threshold, we assume the distance to be the critical minimum GDP growth rate itself.



From this optimization, we found big differences of critical minimum growth rate for developed and emerging markets, which is aligned with the notion that emerging markets are growing their economy at a much faster rate than developed markets. Below is a snapshot of four countries' critical minimum growth rate to see the contrast.

The second threshold is called the default threshold, which is the same CDS-inferred DGR threshold that is used in the Default Probability Simulation (4.2) method. Symmetrically, we applied the 1.5x buffer on the developed market same as in section 4.2.

After getting these two thresholds, we project future DGR time series historical data we got to model the projection will help us determine the year in the future of when that default event for each of the four climate scenarios would happen.

The first approach is the *Default Probability Test*. We run the Default Probability Simulation (4.2) method and test in which year each scenario's probability of default exceeds 50%. For this approach we only take the default threshold. We will run the simulation every year from 2023 to 2050 and check on every year's default probability. The result in section 5.1 will only showcase simulation for 2030 and 2050.

The second approach is called *Three-Factor Model* inspired by Collender et al., (2022), which include auto-regression (AR1) of DGR to lagged times-series variables that are available for these 18 countries, which are: 1) CO_2 emission/Greenhouse Gas (*GHG*), 2) total natural resource rent (*Rent*), and 3) renewable energy (*New*) consumption. We do 4 regressions: ΔGHG, $\Delta Rent$, ΔNew on its lagged values to get 3 regression coefficients of each factor $\beta_{GHG}, \beta_{Rent}, \beta_{New}$ *to project* GHG_{t-1}, $Rent_{t-1}$, and New_{t-1}; *and* the ΔDGR on its lagged value and the ΔGHG, $\Delta Rent$, ΔNew to get β_{DGR}. These regression coefficients are added as adjustment to *DGR* regression to DGR_{t-1} to form a *DGR* future path.

$$Adjustment = \Sigma\, \beta_{DGR} \times (\mathrm{GHG}_{t-1\ R} + \mathrm{Rent}_{t-1} + \mathrm{New}_{t-1})$$

$$DGR_{t-1,i} = (\beta 0 + DGR_{t-1} * \beta_{DGR} + Adjustment) * multipier_i$$

After getting the path, we split the paths into four different scenarios (i) by adjusingt the severity of the four paths according to Swiss Re (2021) paper. This will then give different severity adjustment for each country, depending on how worse GDP loss projection in each climate scenarios, For base case, i.e., no penalty, we assume that DGR will remain constant for the level of 2022.

5. Model Results

5.1 Default Probability Simulation

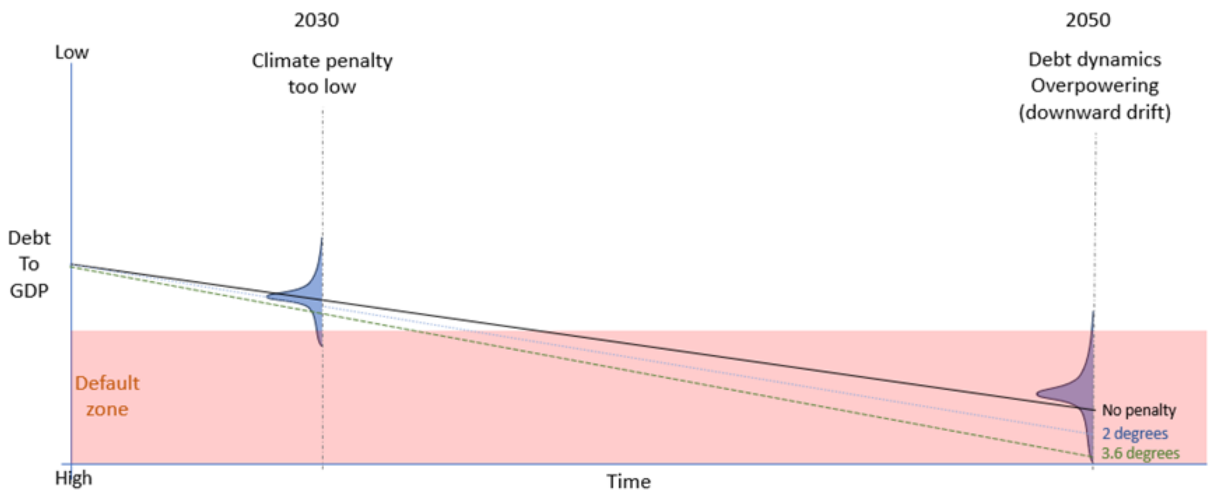
We assess the effect of climate risk on 18 sovereign bonds by looking into key scenarios (1.5°, 2°, 2.6°, 3.2° in temperature increase by 2050) and important dates (2030,2050).

From our calibrated debt / GDP generation model, we simulated 10000 paths each for 4 scenarios, and calculated the probability of paths falling under the defaulting-DGR ratio. Then we try to isolate the climate risk in terms of default probability using the spread against the no climate risk penalty scenarios.

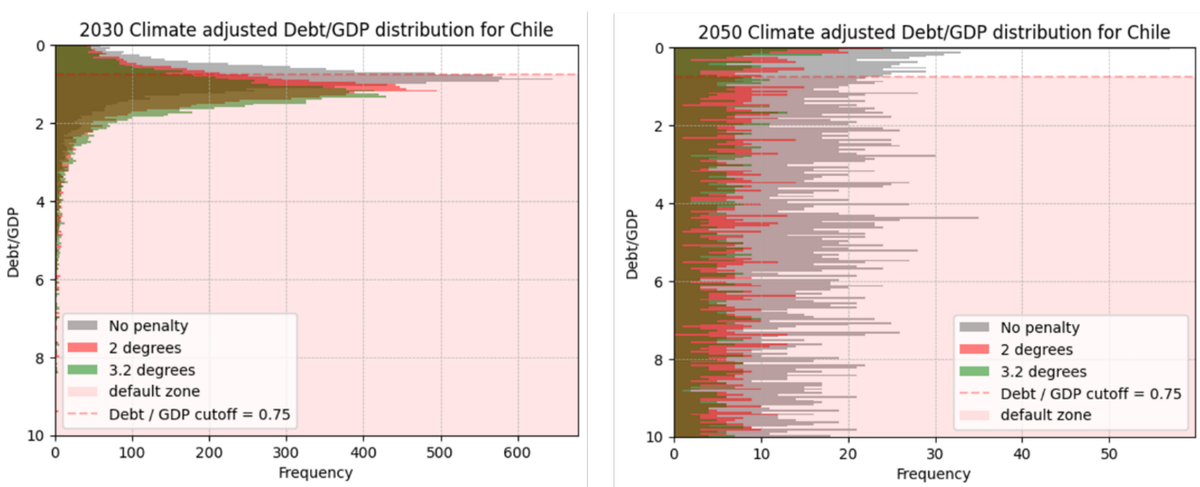
The transitional risk assumes that the transitional efforts to combat climate change are exogenously determined, thus we have the same amount of penalty on debt dynamics across each climate scenario, effectively demonstrating a parallel shift from the base case scenario. We can easily extrapolate the transitional risk effect from the comparison between the base case scenario and the 1.5° scenario.

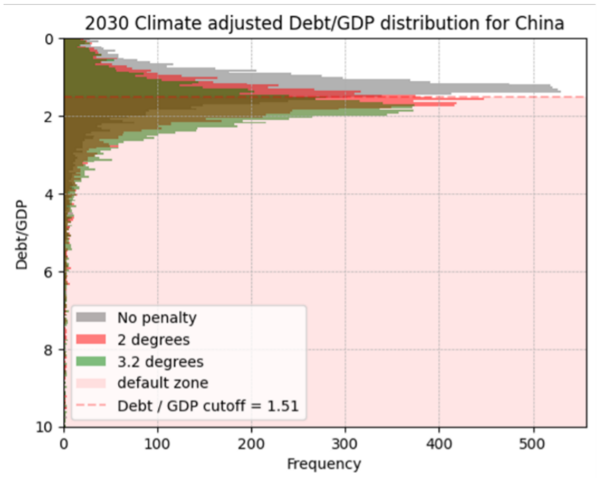
The physical risk, however, holds different magnitudes across the different scenarios. When we compare the default probability difference across climate risk scenarios (1.5°, 2°, 2.6°, 3.2°) the difference is driven merely by the physical risk.

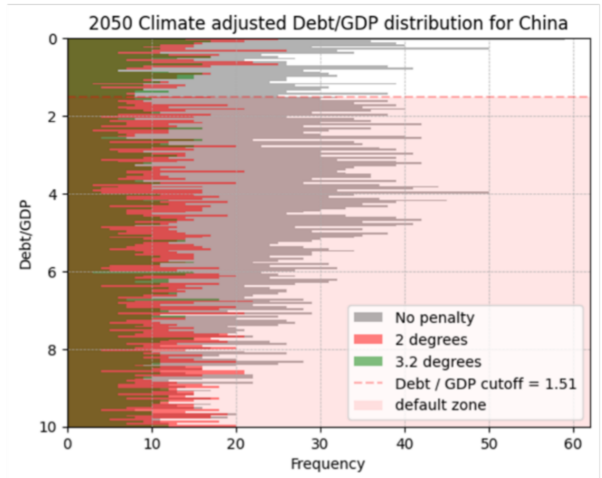
From the post climate penalty DGR distribution of each country, we attempt to analyze the climate risks effects driven by transitional risk and physical risk for each country, however one thing to note is that the climate risk is maximized when the mode of the DGR distribution is close to the DGR / default threshold, where a small parellel shift down the distribution has a meaningful amount of area is moved into the default zone, as depicted in the graph below:

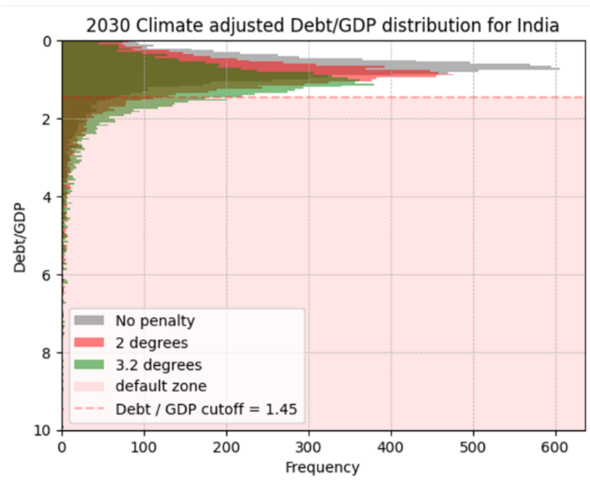


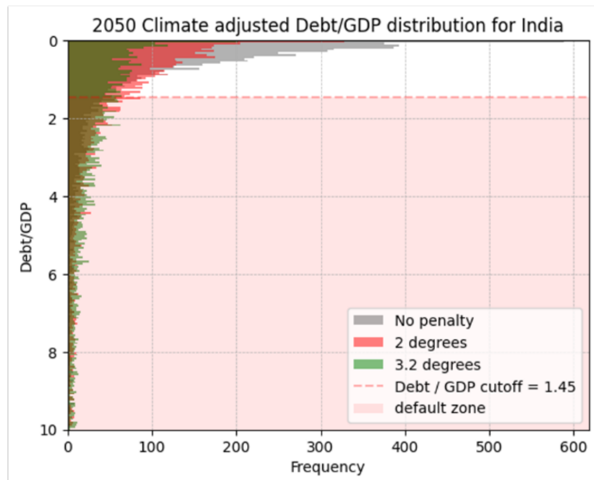
5.1.a. Undeveloped Countries

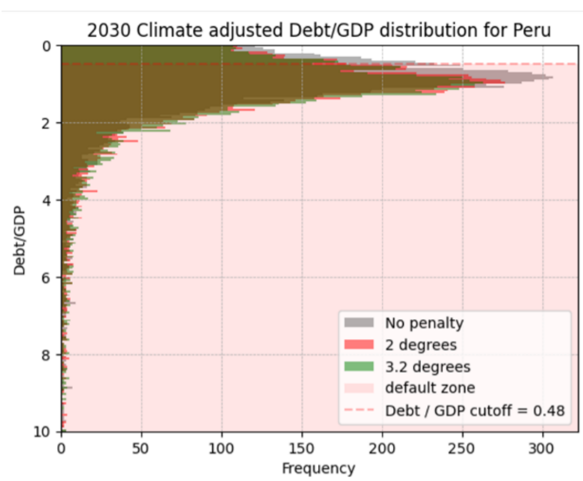


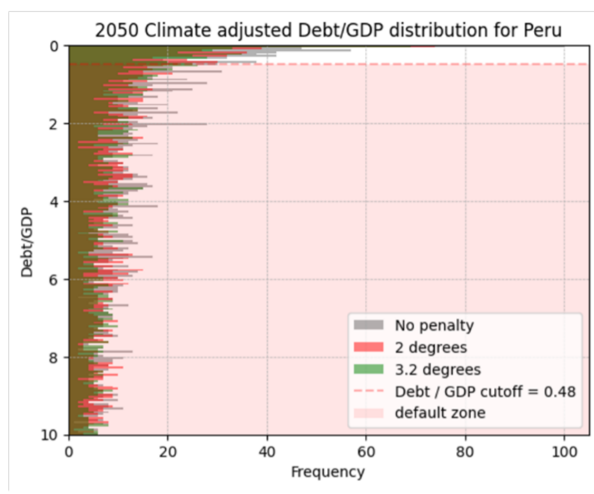

2030 Climate adjusted Debt/GDP distribution for China
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.51


2050 Climate adjusted Debt/GDP distribution for China
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.51
default zone


2030 Climate adjusted Debt/GDP distribution for India
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.45


2050 Climate adjusted Debt/GDP distribution for India
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.45
default zone


2030 Climate adjusted Debt/GDP distribution for Peru
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 0.48


2050 Climate adjusted Debt/GDP distribution for Peru
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 0.48
default zone

As we approach the year 2050, Chile's base case probability of default (PD) naturally increases, aligning with our intuitive expectations. However, an intriguing phenomenon emerges when the temperature rises beyond 2 degrees Celsius – the probability of default unexpectedly decreases. This counterintuitive trend may be attributed to a combination of factors. Economic adaptation and resource abundance could enhance economic stability, while international partnerships and diversification of industries and exports might reduce financial vulnerabilities.

China exhibits an increased probability of default (PD) as it approaches 2050 as well. This suggests that the economic structures of the nation might be vulnerable to the adverse effects of climate change, potentially due to their reliance on climate-sensitive sectors like agriculture and manufacturing, which can be directly impacted by rising temperatures and the resulting disruptions.

For India, the broader spread of debt-to-GDP ratios and the sharper increase in PD under climate scenarios may be reflective of its developmental stage and the existing socio-economic challenges that could be exacerbated by climate-related events. If policies are not in place to buffer these impacts, India could face substantial risk exposure, particularly if its economic growth is not robust enough to withstand the shocks of climate change.

Peru's situation is particularly precarious, with a high PD even in the base case, which climbs further under climate stress scenarios. This could be indicative of a high existing debt level or a vulnerable fiscal structure that climate impacts could strain further.

Chile PD

	2030	2050
Base Case	62.5677	69.3777
1.5	69.8538	70.7355
2	76.2048	71.5253
2.6	76.9129	71.5834
3.2	79.3713	71.975

China PD

	2030	2050
Base Case	29.4096	68.0523
1.5	43.8135	71.1595
2	58.0463	72.9969
2.6	62.2779	73.181
3.2	68.507	73.8097

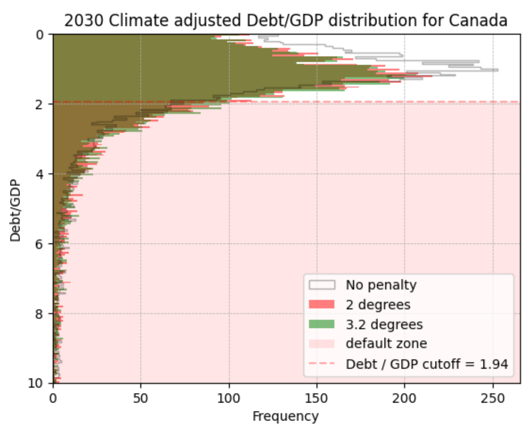
India PD

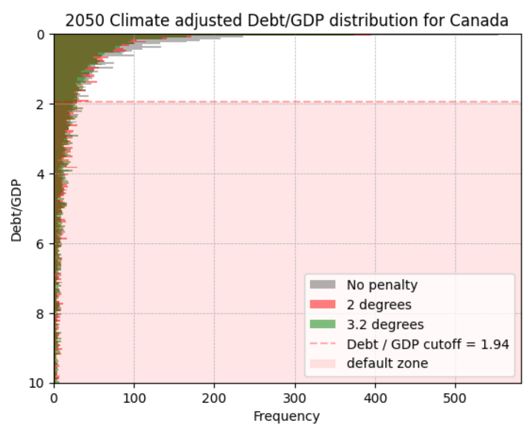
	2030	2050
Base Case	11.1807	17.4775
1.5	13.3098	22.4442
2	17.2887	31.9541
2.6	22.3275	40.5847
3.2	27.7074	46.8425

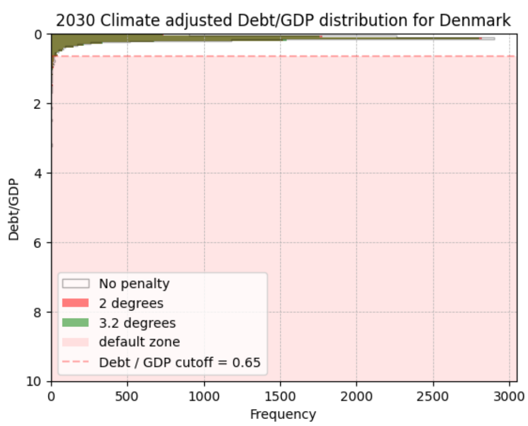
Peru PD

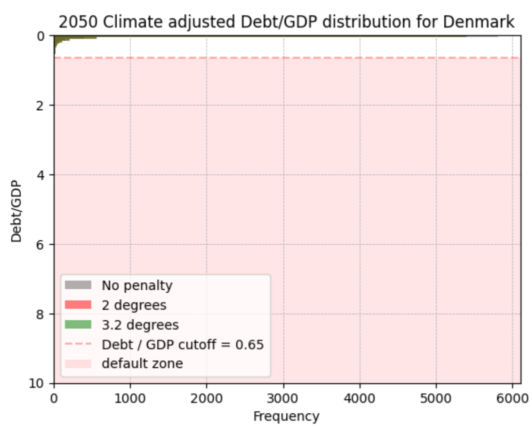
	2030	2050
Base Case	69.418	56.4465
1.5	70.6184	57.0372
2	71.7204	57.3954
2.6	71.9261	57.4846
3.2	72.4623	57.7222

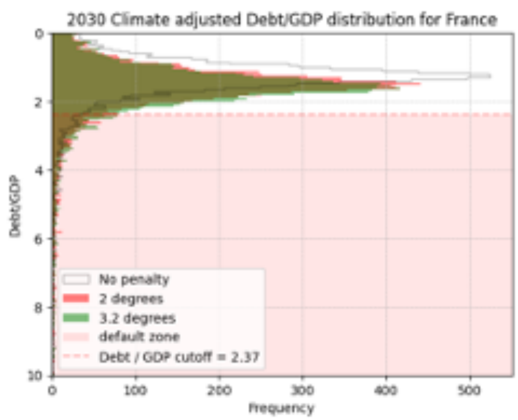
5.1.b. Developed Countries

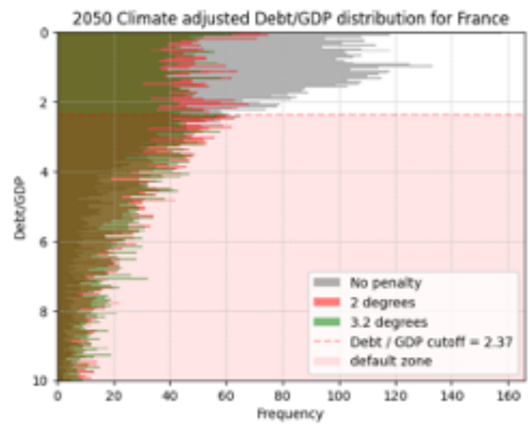


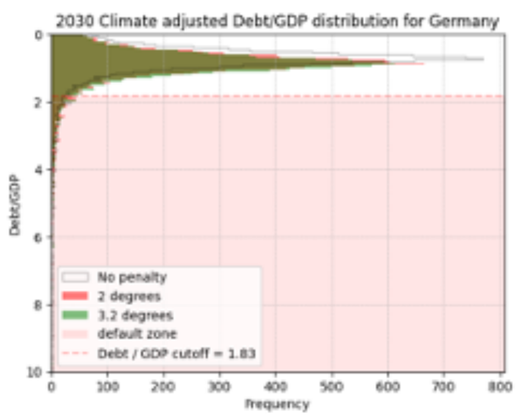


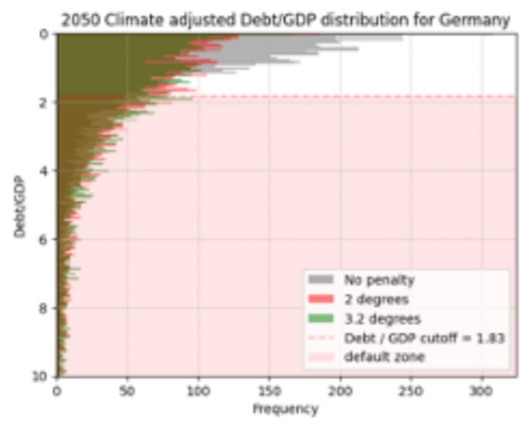


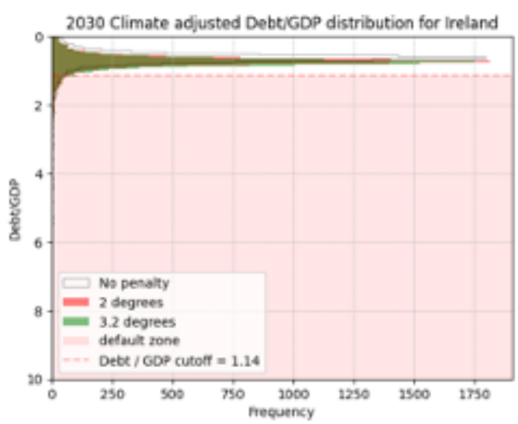


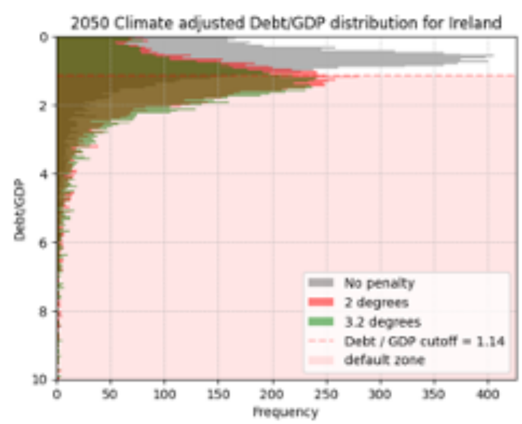

2030 Climate adjusted Debt/GDP distribution for France
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.37

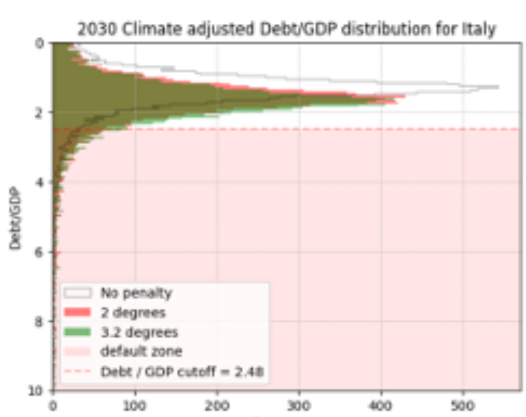

2050 Climate adjusted Debt/GDP distribution for France
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 2.37
default zone

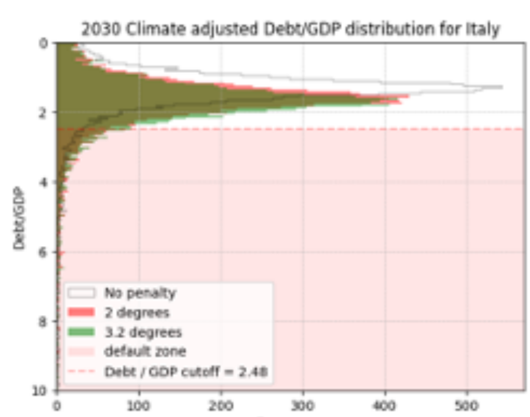

2030 Climate adjusted Debt/GDP distribution for Germany
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.83

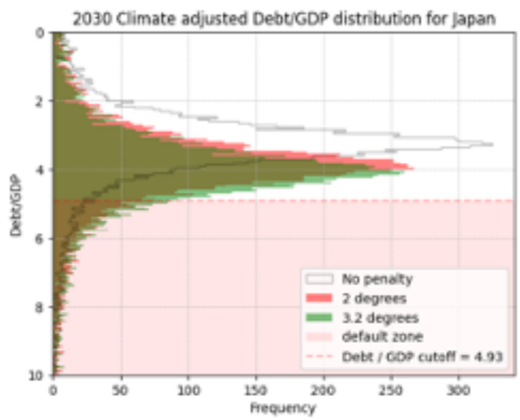

2050 Climate adjusted Debt/GDP distribution for Germany
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.83
default zone

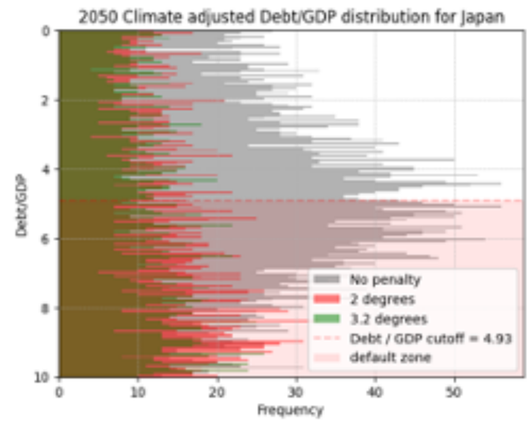

2030 Climate adjusted Debt/GDP distribution for Ireland
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.14

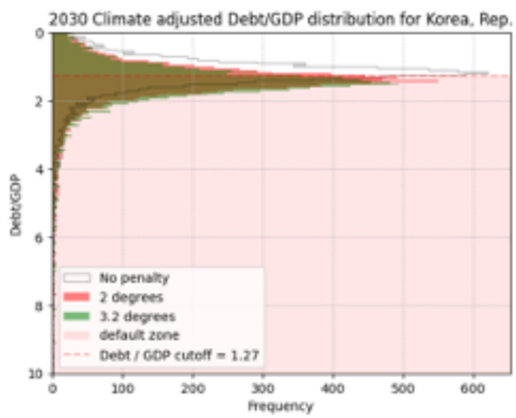

2050 Climate adjusted Debt/GDP distribution for Ireland
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.14
default zone

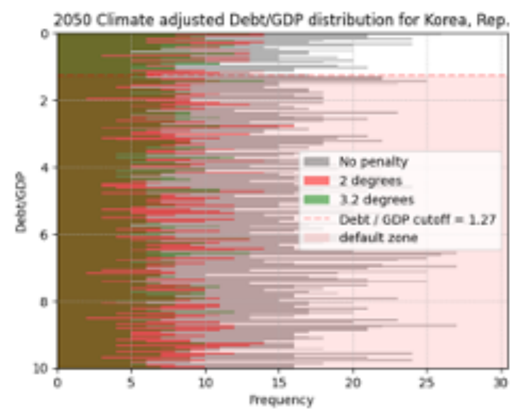

2030 Climate adjusted Debt/GDP distribution for Italy
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.48

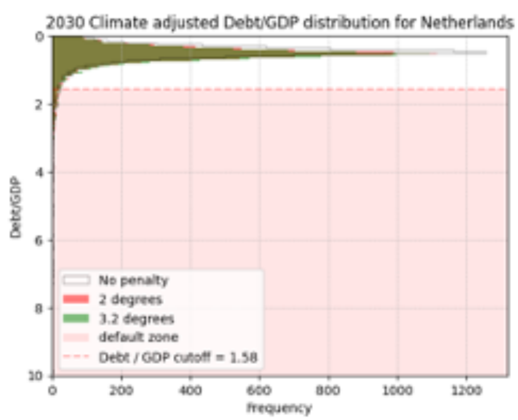

2030 Climate adjusted Debt/GDP distribution for Italy
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.48

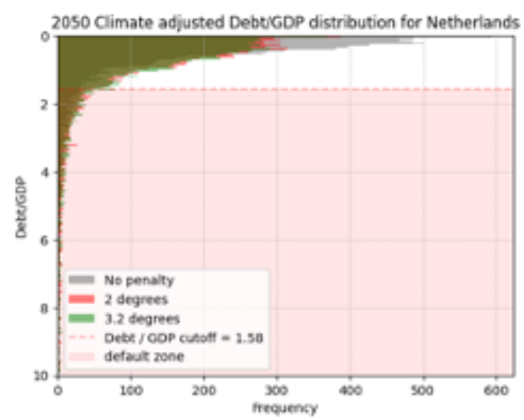

2030 Climate adjusted Debt/GDP distribution for Japan
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 4.93

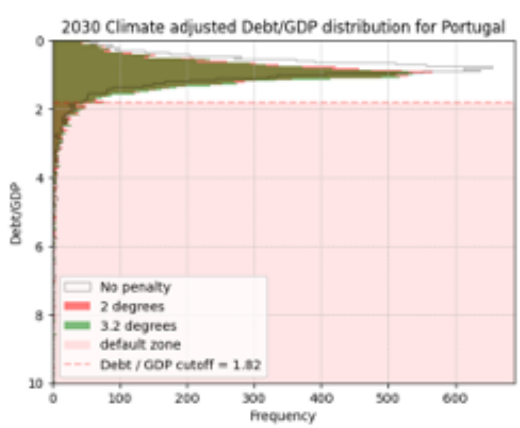

2050 Climate adjusted Debt/GDP distribution for Japan
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 4.93
default zone

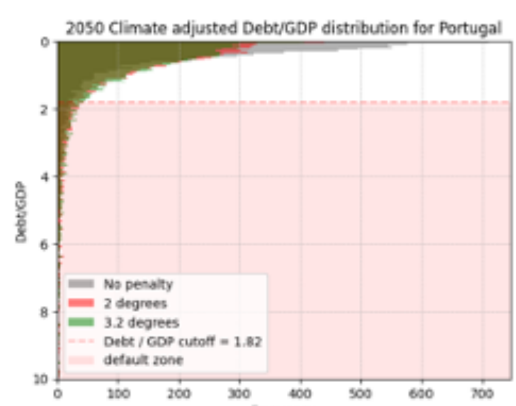

2030 Climate adjusted Debt/GDP distribution for Korea, Rep.
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.27

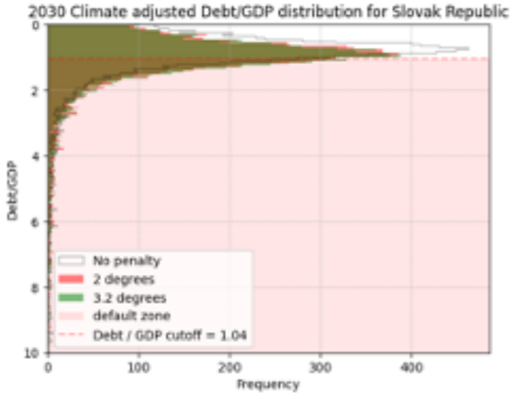

2050 Climate adjusted Debt/GDP distribution for Korea, Rep.
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.27
default zone

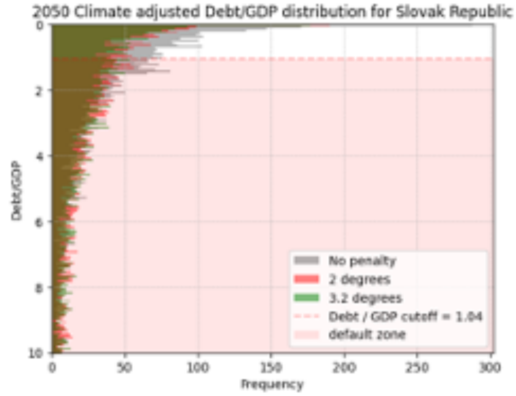

2030 Climate adjusted Debt/GDP distribution for Netherlands
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.58

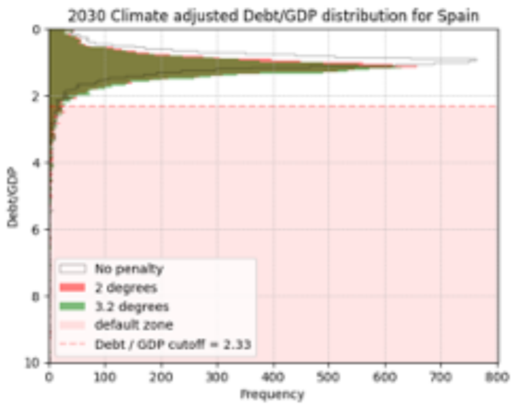

2050 Climate adjusted Debt/GDP distribution for Netherlands
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.58
default zone

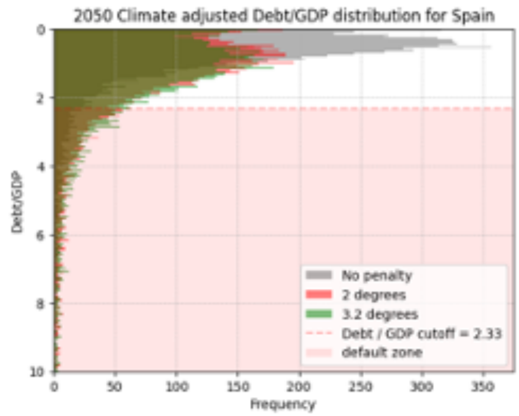

2030 Climate adjusted Debt/GDP distribution for Portugal
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.82

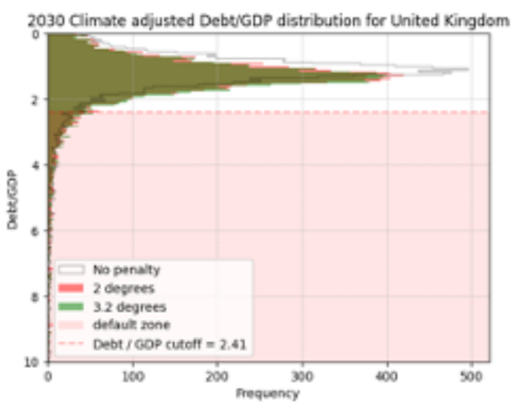

2050 Climate adjusted Debt/GDP distribution for Portugal
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.82
default zone

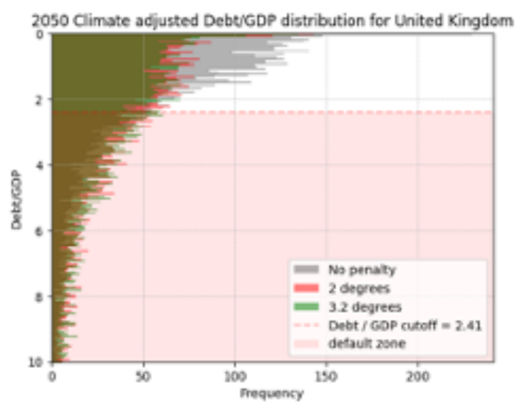

2030 Climate adjusted Debt/GDP distribution for Slovak Republic
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 1.04

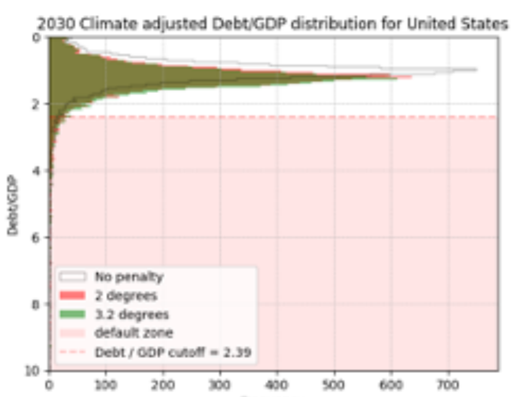

2050 Climate adjusted Debt/GDP distribution for Slovak Republic
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 1.04
default zone

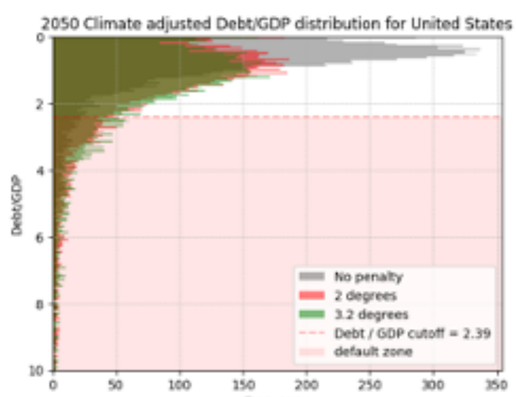

2030 Climate adjusted Debt/GDP distribution for Spain
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.33


2050 Climate adjusted Debt/GDP distribution for Spain
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 2.33
default zone


2030 Climate adjusted Debt/GDP distribution for United Kingdom
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.41


2050 Climate adjusted Debt/GDP distribution for United Kingdom
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 2.41
default zone


2030 Climate adjusted Debt/GDP distribution for United States
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
default zone
Debt / GDP cutoff = 2.39


2050 Climate adjusted Debt/GDP distribution for United States
Debt/GDP
Frequency
No penalty
2 degrees
3.2 degrees
Debt / GDP cutoff = 2.39
default zone

Nations with advanced economies, such as Japan, France, Germany, and Korea, exhibit a progressive increase in the probability of default (PD) as they move from 2030 to 2050 under base scenarios. This trend may reflect the mounting fiscal pressures from climate change mitigation and adaptation costs, even in resilient economies.

Denmark and Spain display relatively lower PDs, yet they are not immune to the upward trend of financial risk by 2050, hinting at the latent long-term fiscal challenges posed by climate change.

Korea and Canada stand out with higher base PDs in the near term, potentially attributable to their existing debt levels, with projections indicating a further exacerbation of risk in the longer term. These patterns underscore the pervasive nature of climate-related economic risks and stress the importance of integrating sustainable fiscal strategies and robust climate policies to safeguard financial stability.

Canada PD

	2030	2050
Base Case	20.4338	25.4226
1.5	24.5709	30.9771
2	26.2156	32.8732
2.6	26.3388	32.9818
3.2	27.3479	34.2074

Italy PD

	2030	2050
Base Case	7.90686	14.94
1.5	10.4677	26.4466
2	12.7572	36.0857
2.6	13.0027	37.0884
3.2	14.7667	42.8785

Japan PD

	2030	2050
Base Case	9.65739	53.1353
1.5	13.4465	67.4173
2	16.8581	71.643
2.6	17.4894	72.012
3.2	20.539	73.8922

Korea PD

	2030	2050
Base Case	37.3322	73.8204
1.5	57.6423	75.5031
2	61.2242	75.7441
2.6	62.6916	75.8437
3.2	66.7021	76.1121

France PD

	2030	2050
Base Case	8.6678	29.7705
1.5	32.4018	67.8776
2	13.2169	51.7051
2.6	13.2169	51.7051
3.2	14.7314	55.451

Germany PD

	2030	2050
Base Case	6.53528	21.6347
1.5	7.61497	31.145
2	8.50304	36.8723
2.6	8.50304	36.8723
3.2	8.89356	40.8341

Netherlands PD

	2030	2050
Base Case	4.08125	11.1716
1.5	4.63844	15.2402
2	4.87077	17.1688
2.6	4.86393	17.0675
3.2	4.98043	18.5122

Portugal PD

	2030	2050
Base Case	7.66505	8.87578
1.5	9.49302	12.8765
2	10.2956	15.1441
2.6	10.3232	15.203
3.2	10.9694	16.4156

Ireland PD

	2030	2050
Base Case	5.44554	22.873
1.5	5.59274	43.4969
2	6.25564	56.1511
2.6	6.24407	55.5988
3.2	6.66346	60.932

Spain

	2030	2050
Base Case	4.92165	9.55763
1.5	5.67158	15.119
2	6.38209	19.7672
2.6	6.46455	20.1368
3.2	6.77991	22.7135

Slovak

	2030	2050
Base Case	28.0205	44.1537
1.5	34.0707	49.1817
2	38.611	51.9061
2.6	38.2871	51.7899
3.2	40.5263	53.0724

Denmark PD

	2030	2050
Base Case	3.23042	1.52601
1.5	3.53697	2.01177
2	3.58106	2.1485
2.6	3.55853	2.129
3.2	3.6007	2.21712

UK PD

	2030	2050
Base Case	8.05794	26.2027
1.5	9.78742	35.7355
2	10.7112	40.4972
2.6	10.6435	40.2508
3.2	11.3655	42.964

US PD

	2030	2050
Base Case	4.85087	9.84663
1.5	5.93974	16.1105
2	6.51159	19.7836
2.6	6.60684	20.5894
3.2	7.04441	23.2489

The charts showcase the projected probability of default (PD) for developed countries across different temperature increase scenarios. An overarching trend is that the PD generally escalates with higher temperature projections, indicating a direct correlation between climate change severity and financial risk.

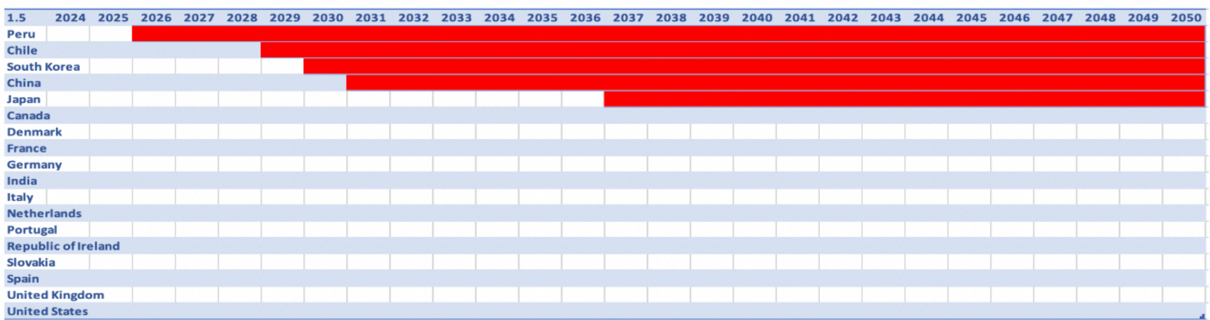
For instance, countries like France and Germany display a significant rise in PD from 2030 to 2050, suggesting that the long-term economic impacts of climate change could be substantial. Conversely, nations like Portugal and Canada show a moderate increase, implying potential resilience due to economic policies or structures. However, besides Denmark, the consistent increase across mostly all countries underscores the pervasive financial challenge posed by climate change, emphasizing the need for proactive strategies to mitigate these risks.

5.2 Time Series of Default

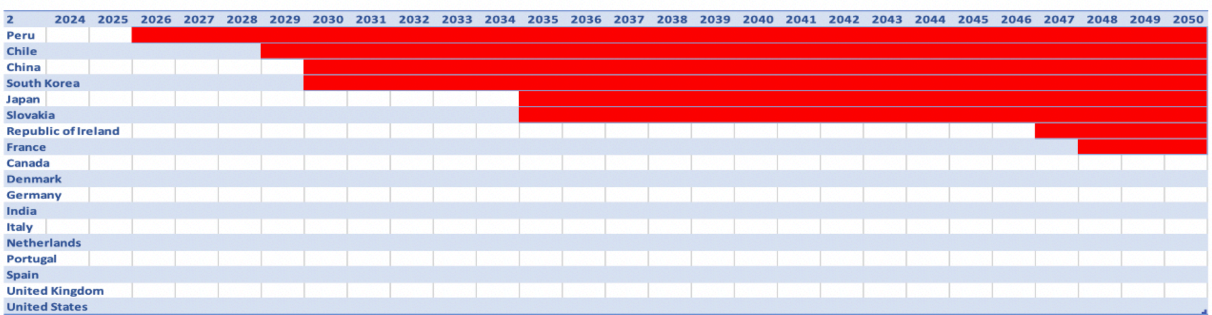
5.2.a. Default Probability Test

The default year test for 18 countries using this method is aligned with the hypothesis that differentiates developed and emerging markets. We can see that in the 1.5 increase, all who are projected to default are emerging markets except for Japan and South Korea. All default timing is relatively early too (2025 to 2037). Meanwhile, for higher temperature increases, we see more developed countries such as Slovakia, France, and the Republic of Ireland. We don't observe any difference from 2.0 and 2.6-degree increases but observe several aggressive moves forward for the scenario 3.2 increase.

1.5° C increase



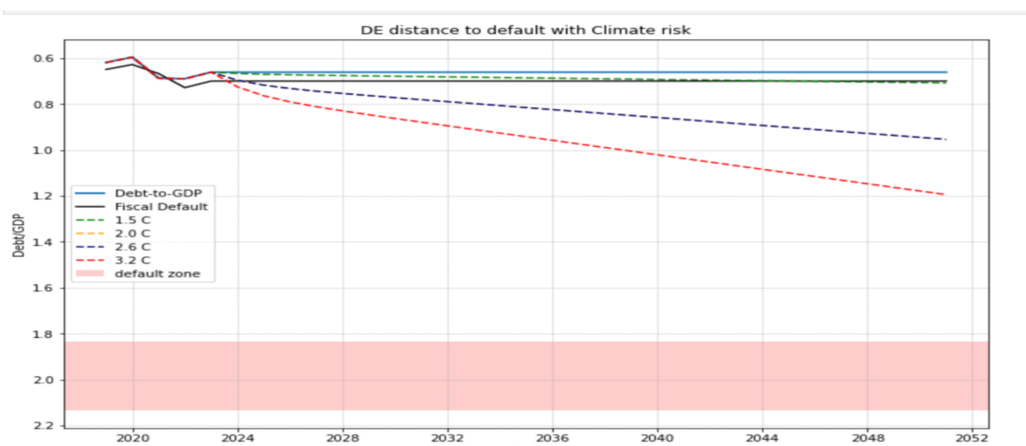
2.0° C increase



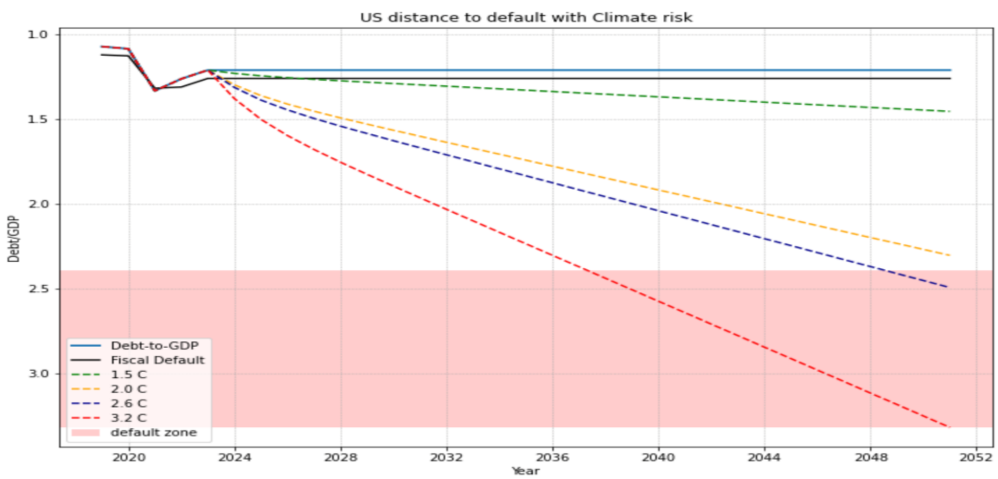
5.2.b Three Factor Model

The fiscal threshold is aimed to predict the timeframe on which each country should be cautious on their debt defaulting. We find that the drivers of default timing for developed and emerging markets are different. For the three-factor model snapshots, we took Germany, United States, Peru and India to portray the different development of this model on different countries. Germany (DE) and United States (US) both have a very tight fiscal space and will almost immediately cross fiscal threshold by 2024 in all scenarios. In the most moderate scenario (1.5 C increase), the US is going to cross the fiscal threshold by 2026 and DE by 2045. In contrast to emerging markets, they have broader fiscal space, yet are still going to cross the fiscal threshold immediately, due to the steep progression of the climate stresses. However, we see that for India (IN) and Peru (PE), they will never cross the fiscal threshold on the most moderate scenario (1.5 C). Followed by aggressive development under other severe stresses (2.0, 2.6, 3.2 C increases). Therefore, we conclude, fiscal threshold is not a very good proxy, as in the two most extreme scenarios most countries cross threshold immediately (2024).

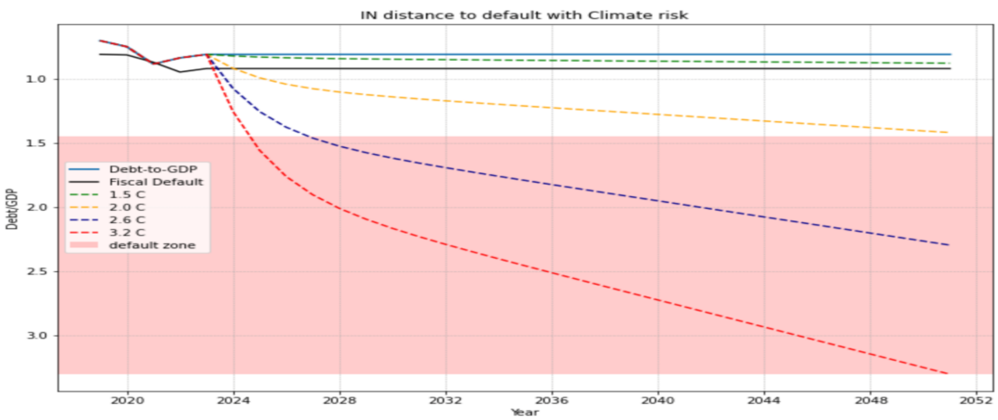
For default threshold, both emerging countries with the most extreme scenarios (2.6 and 3.2) are crossing default threshold before 2050. Under the most extreme scenario, India is projected to default in the near future (2026). Germany is forecasted to not default before 2050 in all scenarios. Meanwhile, the US, as a developed nation anomaly, will cross the default threshold in 2037 (3.2 increase) and 2048 (2.6 increase). In general, developed market scenarios are seen to be more moderate, an anomaly for the US since paths are very steep after 1.5 increase.



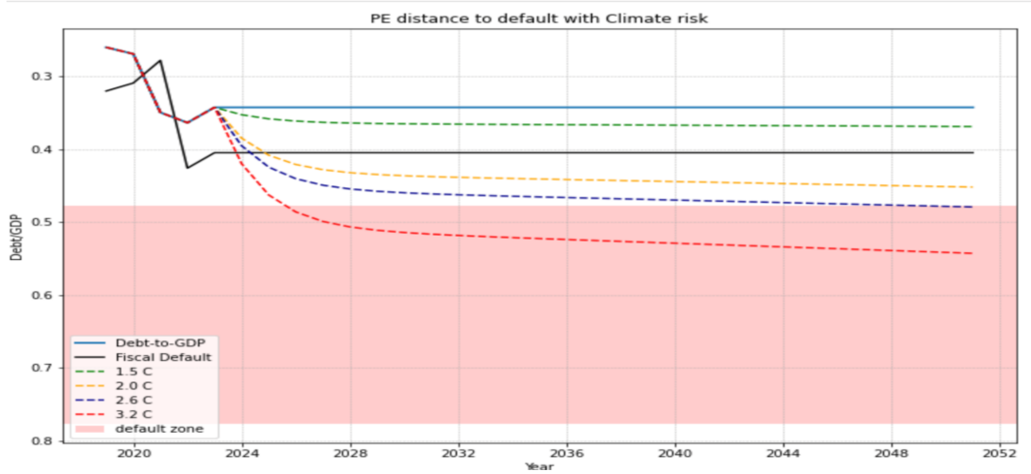
Germany is well-positioned to address the challenges of climate change, and the risk of sovereign default is low due to several key factors. The country has a robust and diversified economy, characterized by fiscal prudence and effective economic management. Germany's commitment to the transition to renewable energy, known as the "Energiewende," showcases its dedication to sustainable practices. The nation's strong emphasis on technological innovation, participation in international cooperation efforts, and ambitious climate policies further contribute to its resilience. Its proactive approach to mitigating GHG emissions, coupled with its strong economic foundation, positions it as a leader in the global effort to combat climate change, reducing the likelihood of sovereign default.



Climate change scenarios present a substantial risk to the United States of America (USA), with a primary concern being the transition risk associated with the nation's high GHG emissions. As a major contributor to climate change, USA faces increasing pressure to transition to a low-carbon economy. This transition, while essential for mitigating climate change, carries economic implications that will elevate the country's debt-to-GDP ratio and may lead to sovereign default in the future. The costs associated with reducing GHG emissions, implementing sustainable practices, and adapting to a changing climate can strain public finances, particularly if not met with strategic fiscal planning. The nation is also facing a heightened frequency and intensity of extreme weather events like hurricanes and wildfires, imposing significant strain on its economy.



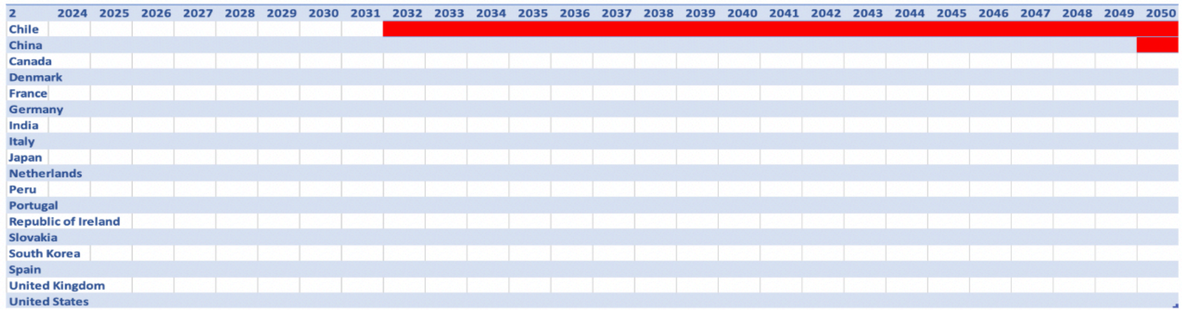
We observe that under the 3.2° C scenario, India is going to experience a very early onset of default due to a large increase in its DGR. Given that historically, India has a hot climate, climate change is anticipated to have profound implications for the country, impacting sectors crucial to economic stability. Increasing temperatures, extreme weather occurrences, and shifts in precipitation patterns have the potential to negatively impact agriculture, water availability, and overall workforce productivity. Additionally, the need for India to transition to renewable energy sources to mitigate climate change may necessitate substantial investments. The costs associated with transitioning to cleaner energy alternatives could strain the country's fiscal resources, potentially contributing to an increase in its debt levels, and eventually leading to default.



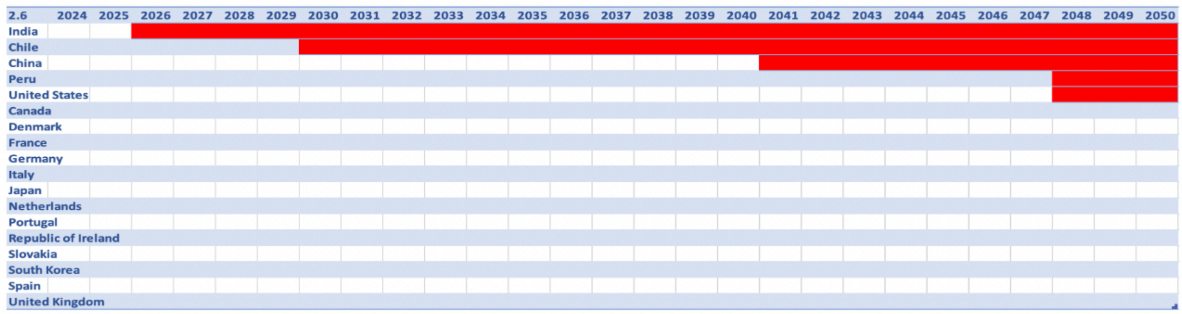
Similarly, the various scenarios pose a multifaceted threat to Peru, which is a low to middle income country. It faces increased vulnerability to extreme weather events, which could damage critical infrastructure and disrupt economic activities. With a substantial reliance on agriculture, changes in climate patterns may harm crop yields, leading to food shortages and increased government spending on recovery efforts. Glacial melting and water scarcity, combined with health impacts and coastal infrastructure vulnerabilities, further strain public resources. Moreover, the need for climate adaptation and mitigation measures, such as resilient infrastructure and renewable energy transitions, may contribute to rising debt levels and hence, we see an early onset of default.

We visualize the result in a grid like the one in 5.1 as we apply the three-factor model for all 18 countries. For this approach, we see a very contrasting result for each worsening climate scenario. First, we see no default event under 1.5 C increase. Under 2.6 C scenario, we can see that all countries that are projected to default are emerging markets, with high real GDP growth rate. However, in the 3.2 scenario, we see that United States and the United Kingdom are ranked just below China and are projected to default in 2037 and 2038 respectively. Meanwhile, all the countries that will never default in all scenarios are all developed countries (South Korea, Slovakia, Republic of Ireland, Netherlands, and Germany).

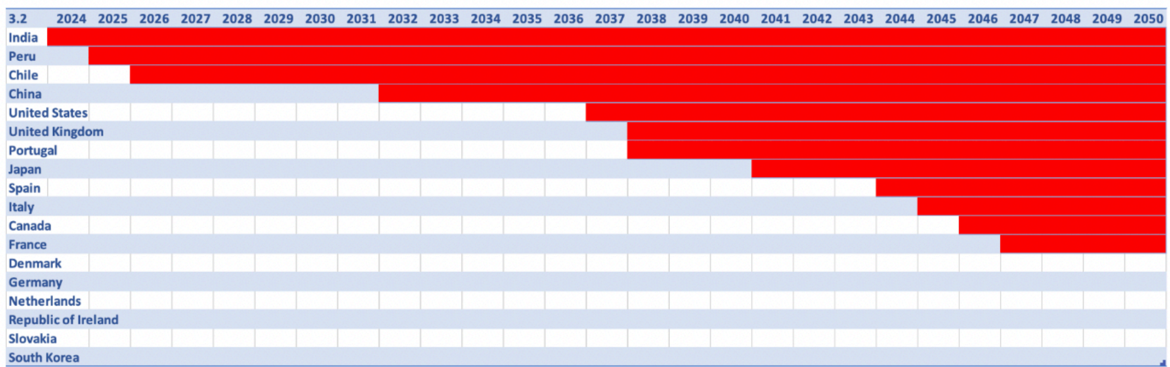
2° C increase



2.6° C increase



3.2° C increase



6. Conclusions

We have applied two methods across the same set of 18 nations, and depending on the properties of the methods we apply, show slightly different results. In the below analysis, we compare the commonalities and key differences of results generated from our two methods to evaluate the climate risks spread in sovereign bonds.

1. In both methods, the emerging countries show relative weakness against climate risks, thus when measuring sovereign risk for EM countries, climate risk modelling should be a key factor to accurately model sovereign spreads
2. In the simulation with climate penalty method, we assume that each year of GDP growth and Debt growth are i.i.d., thus exposes several DM countries with deteriorating fiscal status to more climate risk. As base case default rate enlarges, the climate risk plays out as a larger factor in determining default probability.
3. In the 3-climate-factor Autoregressive method, the autoregressive factor kicks in for the DGR projection, mellowing down the climate risk for the same set of DM countries, returning similar relative climate risk, while the magnitude of climate risk is significantly less.

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