Rising Temperatures, Falling Ratings: The Effect of Climate Change on Sovereign Creditworthiness[*]

Patrycja Klusak[ab], Matthew Agarwala[bc†], Matt Burke[d], Moritz Kraemer[ef], and Kamiar Mohaddes[g]

[a] University of East Anglia, UK
[b] Bennett Institute for Public Policy, University of Cambridge, UK
[c] Centre for Social and Economic Research on the Global Environment, UEA, UK
[d] Smith School of Enterprise and the Environment, University of Oxford, UK,
[e] Centre for Sustainable Finance, SOAS, UK & [f] Goethe-University, Frankfurt, Germany
[g] Judge Business School & King's College, University of Cambridge, UK

January 20, 2023

Abstract

Enthusiasm for 'greening the financial system' is welcome, but a fundamental challenge remains: financial decision makers lack the necessary information. It is not enough to know that climate change is bad. Markets need credible, digestible information on how climate change translates into material risks. To bridge the gap between climate science and real-world financial indicators, we simulate the effect of climate change on sovereign credit ratings for 109 countries, creating the world's first climate-adjusted sovereign credit rating. Under various warming scenarios, we find evidence of climate-induced sovereign downgrades as early as 2030, increasing in intensity and across more countries over the century. We find strong evidence that stringent climate policy consistent with limiting warming to below 2°C, honouring the Paris Climate Agreement, and following RCP 2.6 could nearly eliminate the effect of climate change on ratings. In contrast, under higher emissions scenarios (i.e., RCP 8.5), 59 sovereigns experience climate-induced downgrades by 2030, with an average reduction of 0.68 notches, rising to 81 sovereigns facing an average downgrade of 2.18 notches by 2100. We calculate the effect of climate-induced sovereign downgrades on the cost of corporate and sovereign debt. Across the sample, climate change could increase the annual interest payments on sovereign debt by US$ 45-67 billion under RCP 2.6, rising to US$ 135-203 billion under RCP 8.5. The additional cost to corporates is US$ 10-17 billion under RCP 2.6, and US$ 35-61 billion under RCP 8.5.

Keywords: Sovereign credit rating, climate change, counterfactual analysis, climate-economy models, corporate debt, sovereign debt.

---

[*] We are grateful for constructive comments and suggestions from Franklin Allen, Kevin Aretz, Diane Coyle, Naoki Funada, Stephany Griffith-Jones, Ben Groom, Zeina Hasna, Raphael Markellos, Ellen Quigley, Nick Robbins, Nina Seega, Richard Tol, Uli Volz, Dimitri Zenghelis, and colleagues across the INSPIRE network as well as seminar and conference participants at the Bank of Spain, the World Bank, Bank of England, Cambridge Judge Business School, National Institute of Economic and Social Research, Citi, Inter-American Development Bank, and the European Central Bank. We would also like to thank the Editor and the Associate Editor in charge of our paper, and four anonymous referees for helpful suggestions. We acknowledge funding from INSPIRE. Matthew Agarwala acknowledges financial support for the Bennett Institute Wealth Economy Programme.
[†] Corresponding author. E-mail address: mka30@cam.ac.uk

1. Introduction

Climate change is "the biggest market failure the world has seen" (Stern 2008), with wide-ranging implications for stability – financial, economic, political, social, and environmental. Leading climate-economy models estimate economic losses from climate change of between 2% and 22% of gross world product by 2100 (Burke et al., 2015; Dell et al., 2014; Kahn et al, 2021). Beyond impacts on aggregate output, the environmental, social and policy consequences of climate change will directly impact firms, investors, and regulators. Possible transmission pathways include physical damages from extreme weather events, consumer movements (including boycotts, protests, in reputational risks), transition risks (e.g., from regulations and asset stranding), and litigation risks (e.g., lawsuits over environmental damages). Dietz et al. (2016) estimate that the 'climate value at risk' of global financial assets amounts to US $2.5 trillion. Financial markets face growing pressure to factor these climate impacts into decision making and to mobilise capital in pursuit of a Just Transition towards a low carbon future (Fiedler et al., 2021). Whilst enthusiasm for '*greening the financial system*' is welcome, a fundamental challenge remains: investors and businesses lack the necessary information.

To green the financial system, it is not enough to know that climate change is bad. Firms, investors, financial institutions, and regulators need scientifically credible information on how climate change translates into material financial risks, how to price those risks, and how to manage them. Growing demand for climate risk disclosures comes from private investors, activist shareholders, universal owners, public regulators, treasuries and central banks (Deutsche Bundesbank 2019). Investor-led demand for climate risk disclosures has sparked a rapid expansion of the Environmental, Social, and Governance (ESG) ratings market, with approximately $30 trillion, or one-third of all professionally managed assets now subject to ESG criteria (Bloomberg 2021; Howard-Grenville 2021). Regulator-led demand for climate disclosures includes the development of the Task Force on Climate-related Financial Disclosures (TCFD) to improve risk assessments, support better informed capital allocation decisions, and improve short-, medium-, and long-term strategic planning (TCFD 2017). Globally, more than 1,340 companies with a market capitalization of $12.6 trillion and financial institutions responsible for assets of $150 trillion have expressed support for the TCFD (TCFD 2020).

However, the credibility and usefulness of existing climate disclosures is mixed (Mathiesen 2018; Siew 2015). A chief concern is the lack of scientific foundations in climate risk disclosures. Climate models typically operate at the global or national scale, and assess changes in temperature and precipitation over decades or centuries. Translating these projections into material risk assessments on the spatial and temporal scale needed for business and investment decisions remains a challenge (Fielder et al., 2021). Further limitations include a narrow focus on firm behaviour to the exclusion of systemic and macroeconomic context and the incomparability of disclosures across firms and ESG ratings methods (Fiedler et al., 2021; Mathiesen 2018). The result is an overall failure to translate climate science into credible metrics for conveying risks to financial decision makers.

We contribute to closing the gap between climate science and real-world financial indicators. Specifically, we simulate the effect of climate change on sovereign credit ratings for 109 countries under three different warming scenarios, reporting results for the years 2030, 2050, 2070, and 2100. Figure 1 outlines our four-step process for integrating climate economics into sovereign credit assessments and calculating associated changes in the cost of public and corporate debt. First, we develop a random forest machine learning model to predict sovereign credit ratings, training it on macroeconomic indicators and sovereign ratings issued by S&P (2015-2020) to maximise its predictive accuracy. Step 2 adjusts the macroeconomic input data to reflect climate impacts under three future warming scenarios, drawing from cutting-edge climate economics (Kahn et al., 2021) and S&P's own analysis of how environmental change might affect ratings factors (S&P 2015a,b). In Step 3, we feed the climate-adjusted macroeconomic input data into the model created in Step 1, producing the world's first climate-adjusted sovereign credit ratings. Step 4 calculates the effect of sovereign downgrades on the cost of public and corporate debt (Gande and Parsley 2005; Afonso et al., 2012; Almeida et al., 2017). Our goal is to remain as close as possible to climate science, economics, and real-world practice in the field of sovereign credit ratings. To the best of our knowledge, we are the first to simulate the effect of future climate change on sovereign credit ratings, and our approach enables us to evaluate these impacts under various policy and warming scenarios.[1]

[1] S&P (2015a,b) represent the first investigations into the effect of extreme weather and natural disasters on ratings. However, they only include direct damage to property and infrastructure resulting from 1-in-250 year natural disastsers. For an extended review of literature see Appendix A.

Figure 1 Bridging the gap between climate science and financial indicators

Figure 1 describes a four-step process for integrating climate economics into sovereign credit ratings and cost of debt calculations. Step 1 trains a random forest model on macroeconomic input data and sovereign ratings issued by S&P 2015-2020. Macro variables are selected from S&P's ratings method (S&P 2017). Step 2 adjusts the macroeconomic input data for climate change, using Kahn et al. (2021) and S&P (2015a,b). Step 3 feeds climate-adjusted input data into the prediction model generated in Step 1. Step 4 calculates climate-adjusted ratings and associated impacts on the cost of public and corporate debt.

We focus on sovereign ratings for several reasons. First, they are readily interpretable and familiar indicators creditworthiness, already used by investors, portfolio managers, financial institutions and regulators in a range of decision contexts. For instance, ratings are 'hardwired' into decisions over which securities investors can hold (e.g., institutional investors may be committed by their charter not to hold debt below a certain rating (Fuchs and Gehring 2017)). Similarly, under Basel II rules, ratings directly affect the capital requirements[2] of banks and insurance companies (Almeida et al., 2017). Moreover, approximately US$ 66 trillion[3], global sovereign debt accounts for a large share of total assets under management (PRI 2019). As measures of the creditworthiness of this debt, sovereign ratings act as 'gatekeepers' to global markets, significantly influencing the cost and allocation of capital across countries (Cornaggia et al., 2017). Climate change can affect sovereign creditworthiness through multiple channels, including the destruction of physical and natural capital, fiscal ramifications of extreme events as well as adaptation and mitigation investments, reduced productivity, and political instability (Volz et al., 2020; Agarwala et al., 2021).

Sovereign downgrades increase the cost of both public and private debt, influencing overall economic performance (Chen et al., 2016). If climate change reduces sovereign creditworthiness, there could be indirect impacts on other asset classes. One potential

[2] Basel II 'hardwires' ratings into the capital requirements imposed on banks and insurance companies holding specific sovereigns or firms. The rating bins on sovereign claims and their corresponding risk weights are as follows: AAA to AA− (0%), A+ to A− (20%), BBB+ to BBB− (50%), BB+ to B− (100%), and below B− (150%) (Almeida et al., 2017).
[3] Global sovereign debt has expanded significantly during the Covid-19 pandemic, but this pre-dates the present analysis.

mechanism is the 'sovereign ceiling effect,'[4] whereby sovereign ratings implicitly place an upper bound on ratings in other asset classes (Adelino and Ferrera 2016; Almeida et al., 2017; Borensztein et al., 2013). A second and closely related mechanism is the observed 'sovereign spill-over effect', whereby sovereign downgrades are quickly followed by downgrades in other asset classes (Augustin et al., 2018; Baum et al., 2016; Gennaioli et al., 2014). Because both the ceiling and spillover effects are more pronounced for firms and financial institutions whose ratings are closest to the sovereign's, any climate-induced downgrades are likely to have a greater impact on the highest rated firms.

A further motivation for focusing on sovereign ratings is the observation that climate change does not just affect firms individually, it affects countries and economies systemically. Narrow, firm-level assessments that ignore broader climate impacts are necessarily incomplete. For instance, Kling et al. (2021) show that climate vulnerability increases the cost of corporate debt both directly due to impacts on the firm, and indirectly, due to a weaker macroeconomic environment. Combined, the sovereign ceiling, spillovers, size of the sovereign bond market, and the indiscriminate nature of climate change means no corporate climate risk assessment is complete without also considering the effect climate on sovereigns. Finally, because sovereign ratings impact bond yields (i.e., the cost of public borrowing), understanding how they might be affected by climate change is central to long-term fiscal sustainability.

One concern is the time horizon over which climate change might affect sovereign debt markets (Monasterolo 2020; Agarwala et al., 2021). Whilst climate dynamics mean many of the worst effects of warming will accrue long in the future, debt markets may price in these effects earlier. Indeed, a series of seminal papers has provided the initial empirical evidence that climate change is already increasing sovereign borrowing costs, especially for climate-vulnerable countries (Buhr et al., 2018; Kling et al., 2018; Battiston and Monasterolo 2019; Beirne et al., 2021; Zenios 2021). Calculating the impact of climate risk on bond yields for 46 countries from 1996 to 2016, Buhr et al. (2018) find that climate related vulnerability increased the cost of debt of developing countries by 117 basis points, which translates into USD 40 billion in

[4] For example, following a sovereign downgrade of Italy on the 28th April 2020, Fitch downgraded four Italian banks: UniCredit S.p.A.'s, Intesa Sanpaolo's (IntesaSP), Mediobanca S.p.A.'s , and Unione di Banche Italiane S.p.A.'s (UBI) (Fitch 2020). Similarly, Moody's downgraded 58 sub-sovereign entities after UK's sovereign action 16th October 2020 (Moody's 2020).

additional interest payments on government debt over the past 10 years. Climate may also affect other classes of public debt. Painter (2020) investigates how exposure to sea level rise affects yields for US municipalities, finding that a one percent increase in climate risk leads to an increase in cost of capital by 23.4 basis points, or an average rise in annualized issuance costs of $1.7 million for the average county.

Our results document three key findings. First, we show that under various warming scenarios, climate change could induce sovereign downgrades as early as 2030, with larger downgrades across more countries to 2100. For instance, in absence of climate policies (i.e., RCP 8.5[5] scenario), 59 sovereigns experience downgrades of approximately 0.68 notches by 2030, rising to 81 sovereigns facing a downgrade of 2.18 notches by 2100. Second, our data strongly suggests that stringent climate policy consistent with the Paris Climate Agreement will result in minimal changes to the current ratings profile. We find that the average rating reduction between 2030-2100 remains unchanged when we subject the mean change between periods to tests of statistical significance.. The additional costs to sovereign debt – best interpreted as increases in annual interest payments due to climate-induced sovereign downgrades – in our sample is US$ 45–67 billion under RCP 2.6, rising to US$ 135–203 billion under RCP 8.5. The additional costs to corporates reach US$ 9.9–17.3 billion under RCP 2.6, and US$ 35–61 billion under RCP 8.5. This suggests that in the absence of climate mitigation and adaptation policies, climate change can ultimately degrade long-run fiscal sustainability and increase public and corporate borrowing costs.[6] We find qualitatively similar results using three independent macroeconometric climate-economy models: Kahn et al. (2021), Kalkuhl and Wenz (2020), and Burke et al. (2015)[7]. Results are robust to changing the time series of ratings used to train the prediction model, restricting the model to only those sovereigns with investment grade ratings, and varying assumptions about the degree of temperature volatility within the baseline climate-economic model.

---

[5] RCPs are Representative Concentration Pathways and describe different potential scenarios of future emissions trends. RCP 2.6 is the ‘stringent climate policy’ scenario and is most consistent with limiting warming to below 2°C. RCP 8.5 is the high emissions scenario and is more consistent with a 4.5°C warming world. See extended literature review, Appendix A.

[6] A full consideration of the net effect of adaptation and mitigation investments on creditworthiness would need to incorporate the fiscal implications of such policies. This is beyond the scope of the current analysis, but remains an important avenue for future research.

[7] Results for Kalkuhl and Wenz (2020) and Burke et al. (2015) are available upon request.

These results are of interest to finance ministries and central banks, regulators (e.g., ESMA and the SEC), banks, insurers, and institutional investors. Climate-induced sovereign downgrades provide a direct and immediate financial incentive for sovereigns to pursue climate-smart investments, (e.g., boosting resilience and adaptive capacity) to improve their current rating and reduce the cost of borrowing. The research is timely, as governments seek to balance fiscal stimulus following the Covid-19 pandemic against the need to manage the public finances in the long run. That public investment in low-carbon climate resilient infrastructure presents an attractive long-run growth opportunity is firmly established (Hepburn et al., 2020; Zenghelis et al., 2020). Our results add further support by demonstrating that limiting warming to 2°C or less would improve fiscal positions through two channels: (i) reducing the cost of corporate debt, thereby enhancing competitiveness, and (ii) reducing future interest rates on sovereign debt, thereby maintaining fiscal operating space and reducing future tax burdens.

Our results are of central importance to the regulation of CRAs and development of ESG standards. Although the European Securities and Markets Authority (ESMA, which regulates credit ratings agencies (CRAs) in Europe) has called for greater transparency and disclosure around ESG factors they have refrained from introducing formal requirements (ESMA 2019). Existing climate disclosures and ESG ratings remain largely voluntary and are not standardised. CRAs recognise that climate and environmental factors "could have significant implications for sovereign ratings in the decades to come… [although they] pose a negligible direct risk to sovereign ratings in advanced economies for now, on average, ratings on many emerging sovereigns (specifically those in the Caribbean or Southeast Asia) will likely come under significant additional pressure" (S&P 2018). One potential obstacle is a lack of credible methods for assessing the impact of climate on creditworthiness (Buhr et al., 2018). Our research represents a first step in providing such a method.

The remainder of this paper is as follows. Section 2 describes data and methodology. Section 3 provides empirical results of climate-adjusted sovereign credit ratings. Section 4 discusses additional cost sovereign and corporate borrowing due to climate-induced downgrades. Finally, Section 5 offers some concluding remarks.

2. Data and methodology

2.1. Rating data

Our sample consists of 644 annual long-term foreign-currency sovereign ratings for 109 countries, issued by S&P between 2015 and 2020, obtained from S&P Ratings Direct database.[8] Alphabetical ratings are translated into a 20-notch[9] scale widely used in the literature (Correa et al., 2014; see Appendix Table B.1). Although several agencies issue sovereign ratings, we use S&P's because they have the widest country coverage over the assessment period and their ratings actions have the strongest own-country stock market impact (Almeida et al., 2017; Brooks et al., 2004; Kaminsky and Schmukler 2002). Figure 2 describes the distribution of ratings in 2015 and 2020, and Table 1 describes ratings actions (upgrades or downgrades) issued by S&P over the period. Table 1 shows a relatively balanced distribution of positive and negative rating actions and that the vast majority have a magnitude of 1-notch. The average rating across the sample is 11.14, or BBB-, which is the lowest investment grade rating.

Figure 2 Distribution of sovereign ratings 2015 and 2020

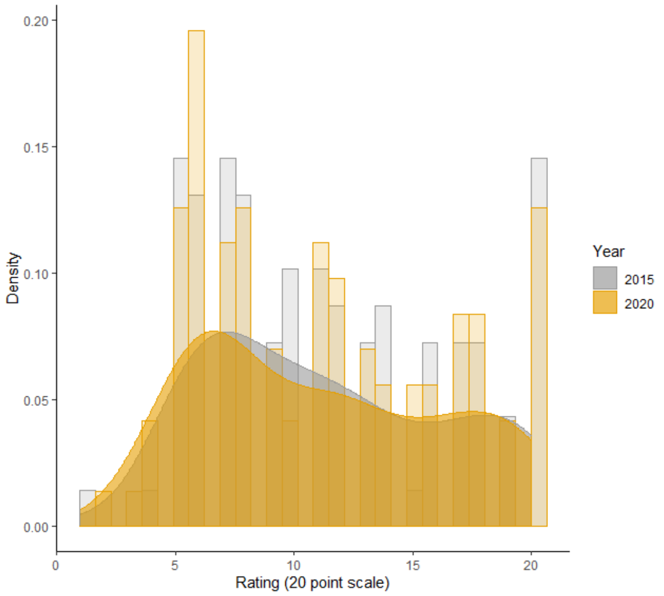

Figure 2 depicts the distribution of annual long-term foreign-currency sovereign ratings for 109 countries, issued by S&P between 2015 (gray) and 2020 (orange). A score of 20 refers to AAA.

[8] In sensitivity checks we trained the prediction model on 1,590 annual long-term foreign-currency sovereign ratings from 2004 – 2020. However, predictive accuracy was highest for the 2015 – 2020 period as the ratings effects of the 2008 financial crisis and the 2009 European sovereign debt crisis had largely dissipated.

[9] Following standard notation, 20 corresponds to AAA, or prime high grade; 11 corresponds to BBB-, and is the lowest investment-grade rating.

Table 1 Sovereign credit rating actions 2015 - 2020

Entire sample		
Countries	109	
Average numerical rating	11.14	*%*
Positive events	**55**	***52.88***
Upgrade by 1 notch	49	*47.12*
Upgrade by 2 notches	3	*2.88*
Upgrade by > 2 notches	3	2.88
Negative events	**49**	***47.12***
Downgrade by 1 notch	37	*35.58*
Downgrade by 2 notches	9	8.65
Downgrade by > 2 notches	3	*2.88*
Total no of events	**104**	***100***

Notes: Table 1 presents summary statistics of S&P's rating actions based on annual sovereign ratings translated into a 20-notch scale from Jan 2015-Jan 2020. Rating actions refer to upgrades or downgrades.

2.2. Macroeconomic data

Sovereign credit ratings incorporate a wide range of objective macroeconomic data and subjective assessments by ratings agencies. Although the science, economics, and politics of climate change are widely studied, we do not have a reliable source of information on how climate change will impact every variable included in the sovereign ratings methodology.[10] Variable selection in our model is based on several factors: relevance for predicting ratings, the availability and quality of scientific evidence describing how they respond to climate change, and country coverage. This approach avoids overfitting and ensures our model inputs remain as close as possible to the underlying climate science and economic models. Our baseline climate-economy model (Kahn et al., 2021) provides estimates of climate-adjusted real GDP growth rates and levels up to 2100.

Table 2 presents cross-sectional descriptive statistics of the six macroeconomic variables used in our analysis. Data comes from S&P Ratings Direct Sovereign Risk Indicators (SRIs). Countries in the sample display a wide range of income levels, growth rates, and macroeconomic performance indicators.

[10] For example, De Moor et al. (2018) and Ozturk et al. (2016) employ 23 and 16 variables to predict ratings. See the literature review in Appendix A.

Table 2 Summary statistics

Variable	Mean	St. Dev.	Min	Max
Log GDP per capita (log US $)	9.09	1.30	6.03	11.70
Real GDP Growth	3.09	2.63	-9.77	25.16
Government performance variables				
Net General Government Debt/GDP	36.47	64.67	-489.79	172.82
Narrow Net External Debt/CARs	61.18	124.70	-708.18	461.29
Current Account Balance/GDP	-1.51	7.48	-63.50	33.44
General Government Balance/GDP	-2.60	3.80	-21.05	21.57

Notes: Table 2 presents summary statistics for the natural logarithm of nominal GDP per capita in US $ (Log GDP per capita US$), the annual nominal growth rate (GDP Growth), net general government debt/GDP, narrow net external debt/current account receipts (CARs), current account balance/GDP, and general government balance/GDP. Data from 2015 - 2020.

Our commitment to climate-science underpinnings entails a trade-off: we are unable to include some important determinants of ratings such as political stability and government transparency because we do not have credible science-based descriptions of how they vary with climate. Including them in the model improves predictive capacity in step one, as per De Moor et al. (2018) and Ozturk et al. (2016). However, because we cannot adjust them for climate change, in step two the prediction model simply anchors to these (artificially) non-varying indicators. Indeed, the anchor effect can be sufficient to dominate all other economic indicators. There is no credible basis for assuming that political stability is in fact climate-invariant, or that growth and debt related factors will cease to drive ratings. As such, we are restricted to pursuing the greatest possible predictive accuracy using only the variables that we can credibly adjust for climate change. The method is readily extendable when empirical measures of how climate change will impact political stability become available.

2.3. Methods

We construct a sovereign ratings prediction model based on S&P's sovereign ratings and the 6 ratings factors defined in Table 2 over the period of 2015-2020. This reflects a relatively stable period, though for completeness, we also trained the prediction model on data from 2004 – 2020. Out-of-sample tests indicated that predictive accuracy was highest for the 2015 – 2020 period as the ratings effects of the 2008 financial crisis and the 2009 European sovereign debt crisis had largely dissipated.

Once the initial model has been trained on the 2015-2020 data, we use it to predict sovereign credit rating outcomes under various climate scenarios. This is achieved by adjusting the model's six ratings factors for future climate impacts. Climate-adjusted GDP and GDP growth rates are taken directly from Kahn et al. (2021). Due to the nature of macroeconometric climate models, our results focus primarily on economic losses arising from physical impacts of climate change. That is, we do not capture transition or litigation risks, including the possibility of climate refugees, civil unrest, or political instability. However, our approach can be readily extended to incorporate these impacts when credible quantitative estimates are available. As such, our results may be considered lower-bound estimates of the effect of climate change on sovereign ratings.

Beyond GDP, sovereign ratings include a range of government performance indicators including net general government debt/GDP, narrow net external debt/current account receipts, current account balance/GDP, and general government balance/GDP. To construct climate-adjusted versions of the four government performance variables in our model, we make use of S&P's assessment of the impact of GDP losses on these variables. S&P (2015b) demonstrate GDP losses associated with various climate-related disasters and their associated impacts on government performance indicators. We plot their results and construct 3rd order polynomial models to describe S&P's estimated relationships disaster-driven GDP losses and each of the government performance variables. We then input our climate-adjusted GDP data (Kahn et al., 2021) into these polynomials to derive climate-adjusted government performance indicators for each warming scenario.

Finally, we feed all six of the newly created climate-adjusted macroeconomic indicators to our prediction model to simulate the effect of climate on ratings. For comparability with the literature and to demonstrate the effect of strict climate policies that are consistent with meeting the Paris Agreement, we present results under four warming scenarios: RCP 2.6, RCP 8.5, and both of these, but allowing the variability of temperature around its long-run average to rise with temperature.

2.3.1. Reconstructing sovereign credit ratings

Our sovereign ratings prediction model is constructed using supervised machine learning methodologies recently applied in this literature (Ozturk et al. 2016; De Moor et al., 2018; Breiman 2001). This approach offers high precision due to its data mining ability, curbs the need for strong assumptions about functional relationships and distributional properties (normality), limits potential biases and automates the processes (Bennell et al., 2006; Markellos et al., 2016; Li et al., 2020). Earlier approaches to modelling credit ratings relied on parametric estimations such as ordered response models or OLS (see for example, Cantor and Packer 1996; Afonso et al., 2009; 2011; Baghai et al., 2016). Modelling sovereign credit ratings parametrically involves overcoming three natural features of the data. First, sovereign credit ratings are ordinal, and often not normally distributed. There are often discontinuities and a jump effect surrounding the breakpoint between investment and non-investment grade. Second, there are a range of non-linear relationships sovereign credit ratings have with predictors. Third, in our case we attempt to model these outcomes in a panel dataset. Incorporating a parametric model which accounts for these features fails to provide a sufficiently high enough out-of-sample accuracy to justify reliable forecasting with climate adjusted variables.

Motivated by these issues, researchers have considered non-parametric approaches to modelling sovereign ratings. Methodological implementations are varied, which include the application of artificial neural networks (Bennell et al., 2006; Fioramanti 2008; Markellos et al., 2016), decision trees (Markellos et al., 2016), random forests (Ozturk et al., 2016; De Moor et al., 2018) and support vector machines (Van Gestel et al., 2007). The central benefits associated with these approaches are twofold. First, nonparametric approaches are much better at handling non-linear outcomes in the data (Markellos et al., 2016). Second, these approaches can often provide a superior fit (De Moor 2018).[11,12] Random forest algorithms are good at dealing with imbalanced panels and are robust to outliers (Chen et al., 2004; Hastie et al., 2009). In addition, it is suspected that sovereign credit ratings are subject to certain thresholds in various country level predictors, such as GDP per capita (S&P 2017). Therefore, using methodologies that are capable of handling non-linearities and qualitative data are essential.

Random forest models are a subset of classification algorithms. To understand how these apply in our model, we first consider a selection of sovereigns whose creditworthiness is either investment grade or speculative grade. The goal is to classify, or 'split' these entities based on

[11] This relates not only to replicating existing ratings but also predicting future ratings and defaults.
[12] One note of caution is that AI based models do not produce interpretable coefficients and therefore one cannot use these methods to derive sovereign rating determinants and their respective significance (Ozturk et al., 2016; De Moor et al., 2018). This is not problematic in our study as we are not trying to find the respective importance of variables in the model, this issue has been studied in the previous literature (Cantor and Packer 1996; Afonso et al., 2009; 2011; Baghai et al., 2016).

their underlying features. Our model incorporates 6 features – the explanatory variables described in Table 2.

The first step in the prediction model entails selecting the feature (variable) that provides the "best" split of the data, where 'best' entails minimising the error. For instance, assume a threshold value of, say GDP per capita existed, above which all sovereigns are investment grade and below which there are only speculative grade sovereigns, then this feature would provide a split with minimal error. As the number of entities that cross these lines grow, so does the error. This split takes place at the first node (see Figure 3).

Figure 3 The random forest classification process

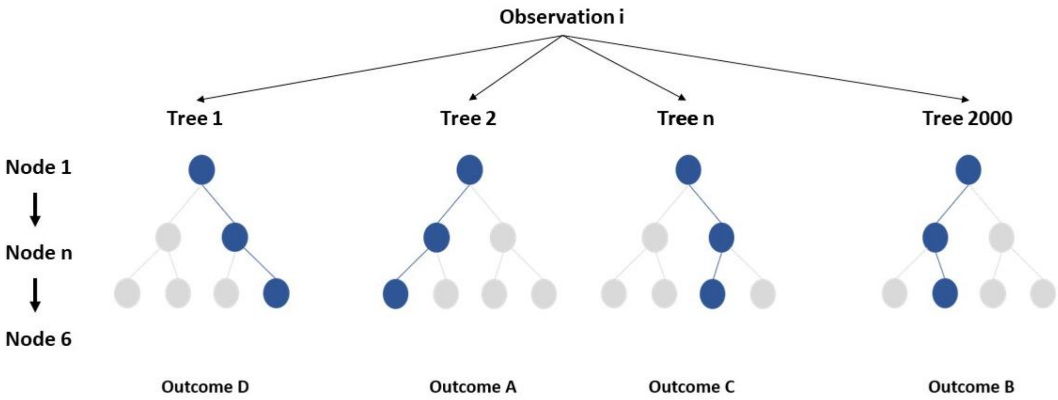

Figure 3 depicts a simplified version the random forest classification process used to predict sovereign credit ratings. For each country, 2,000 trees are constructed, each with 6 nodes. The simplified figure illustrates 4 potential outcomes, though our model contains 20, one for each rung on the 20-notch ratings ladder.

Once data has proceeded through the first split, they each proceed onto their respective next node. The same process repeats itself by which another variable is selected which provides the next best split with the least amount of error. The process of splitting is designed to draw clear boundaries between entities with varying levels of creditworthiness, based upon the values of their features. In our model, we extend this simplified process to 20 different classifications of creditworthiness. Furthermore, the above simplification describes this process only for a single tree. We extend this process to 2000 trees. This process enables the production of a large number of thresholds against which we can test new predictions. The actual model being estimated are these threshold or boundary effects where we can draw distinct lines between the rating categories. This enables several key advantages. First, each tree is modelled upon variations of the initial baseline data. This produces predictions from uncorrelated models, from which we take the average. Secondly, this reduces the common problem of overfitting ultimately resulting in a more accurate out-of-sample prediction. A random forest algorithm enables the tree to select from only a random subset of features. The underlying intuition is that the prediction made by a forest is an average of the decision made by each tree, and as a consequence is much more reliable and robust as a collection.

Machine learning methods are increasingly popular in the sovereign ratings literature and have been employed to model the impact of the informal economy (Markellos et al., 2016), predict sovereign debt crises (Fioramanti 2008), provide accurate predictions of credit ratings (Bennell, 2006; De Moor et al., 2018; Ozturk et al., 2016; Van Gestel et al., 2006) and explain variance in ESG ratings (Berg et al., 2019). In applications of rating prediction, research reports an improvement of accuracy of approximately 30% above parametric approaches (De Moor et al., 2018; Ozturk et al., 2016).

2.3.2. Random forest estimation, variable importance, and partial plots

This section describes how the variables in our model contribute to the ratings estimation. Figure 4 shows the ceterus paribus partial effect of each variable on the sovereign rating. The first graph in Figure 4 (top-left) demonstrates that as ln GDP per capita (US$) increases, the sovereign meets the threshold criteria for increasing rating scores. Furthermore, it demonstrates that ln GDP per capita has non-linear effects on ratings. For instance, at the low end of the rating scale, ln GDP per capita (US$) can continue to decrease with no resulting impact on the rating. At this end of the scale, other variables may be more important for predicting ratings. GDP growth (top-right) has its greatest impact over a much smaller range than per capita GDP and is non-linear. Increases in the growth rate are beneficial in pushing the sovereign further into the investment grade ratings. However, beyond a certain point this effect is lost almost entirely. One explanation may be that unusually high growth rates could be associated with post-shock rebounds, in which case the lingering effects of the shock may dominate the rating. The remaining graphs illustrate the relationships for the government performance indicators.

Figure 4 Marginal effects of credit rating determinants in random forest model

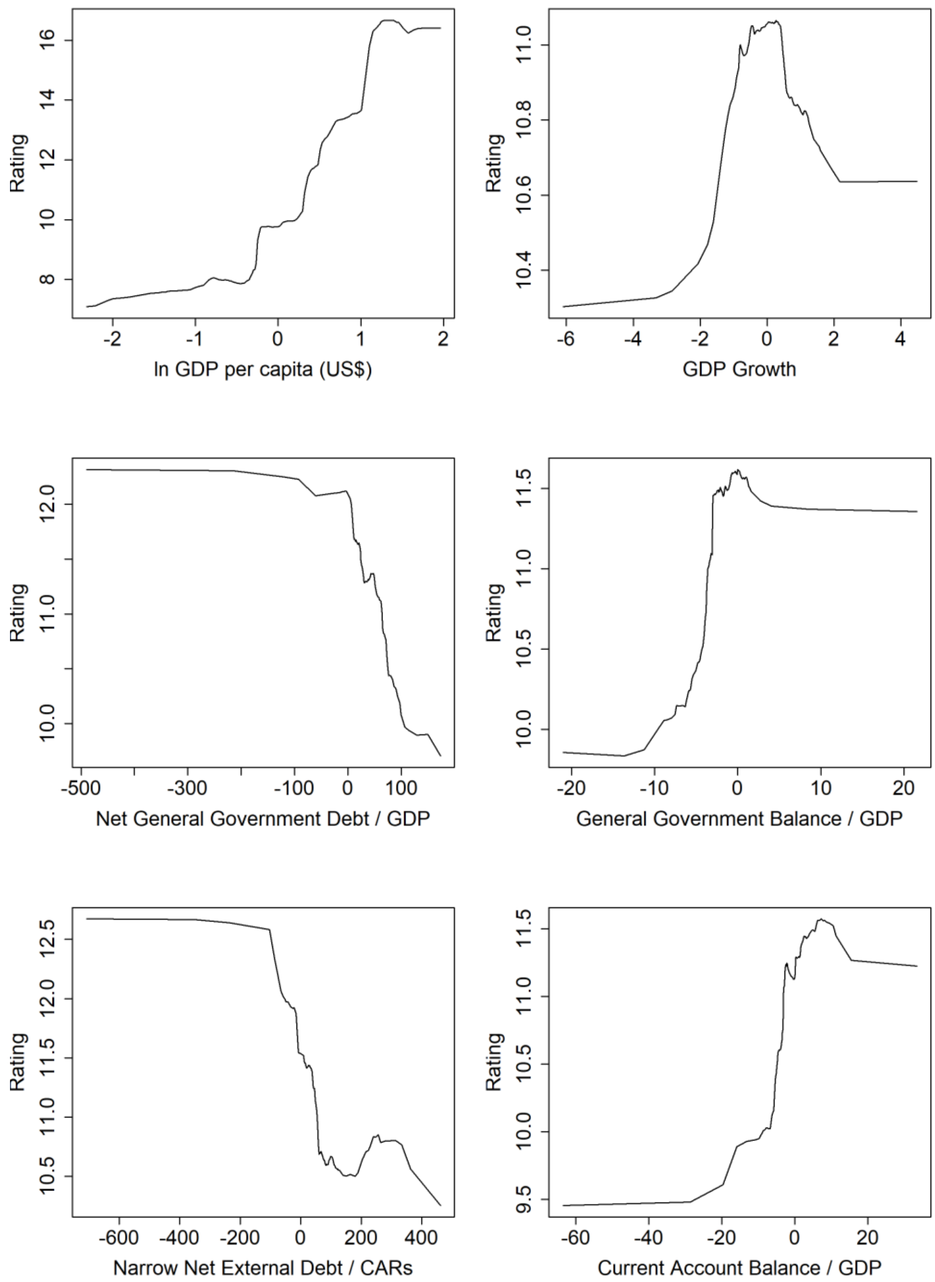

Figure 4 depicts the marginal effect of ln GDP per capita, GDP growth rate, Net General Government Debt/GDP, General Government Balance/GDP, Narrow Net External Debt/CARs, and Current Account Balance/GDP on sovereign ratings. These graphs communicate the ceteris paribus relationship between the variable in the x-axis and the credit rating. These graphs also communicate the relative importance of the variable in the x-axis in determining the credit rating, as represented by the scale in the y-axis.

Figure 5 demonstrates the relative contribution each variable makes to predicting ratings in our model. Formally, it describes the percentage decrease in R^2 that would occur if each individual variables were replaced with random values. The loss in accuracy (percentage reduction in R^2) during this procedure gauges the importance of each variable for predicting ratings. The clear primary driver of predictive capacity is ln GDP per capita, followed by debt measures, government balances, and the growth rate of GDP.

Figure 5 Relative contribution of each variable to ratings prediction.

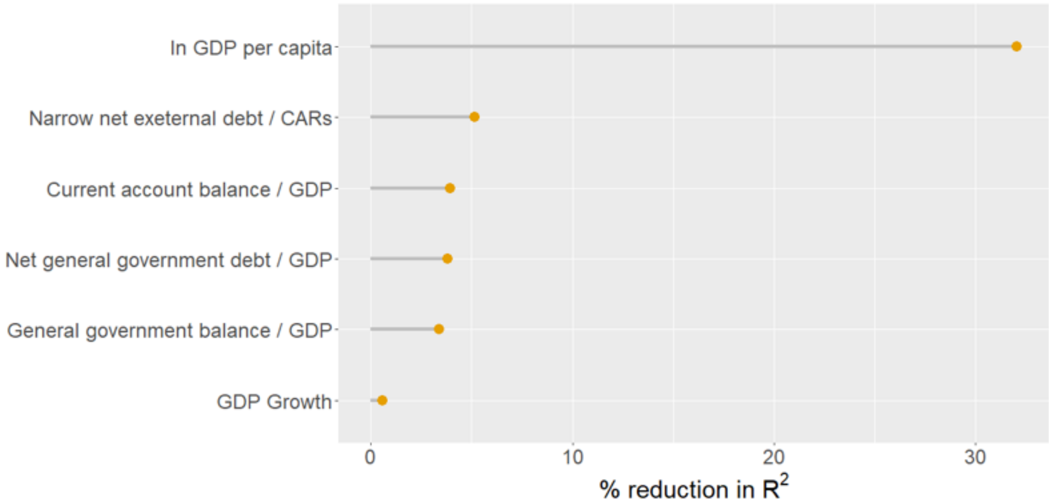

Figure 5 indicates the relative importance of variables in the model. Formally, it depicts the percentage reduction in R^2 that would occur if each variable were replaced by random values. The sample refers to 639 ratings across 109 countries from 2015 – 2020.

Figure 5 should be interpreted as an illustrative measure of the *relative* importance of each variable for predicting ratings across the entire sample. However, whilst the illustrative hierarchy depicted here holds across the sample, in practice it can be expected to vary across countries.

Finally, to demonstrate how each variable in the model contributes to predicted ratings, Figure 6 offers a variable-by-variable breakdown for the G7 plus China. The figure sheds light on how the model predicts ratings for each country. We begin by trying to predict Canada's rating. In the absence of additional information, the first best guess is that Canada's rating is the average predicted rating across the sample, or 11.155. The next row incorporates an additional piece of information: ln GDP per capita. Because per capita GDP in Canada is relatively high, and because this is typically associated with higher ratings, including ln GDP per capita increases the predicted rating by + 5.428 notches to 16.583. In contrast, this step has the opposite effect for China, reflecting the relatively low per capita income. Returning to Canada and incorporating each of the subsequent variables, the predicted rating incrementally improves to 19.672. Figure 6 reiterates the fact that each variable may have different relative contributions to the predicted ratings of individual countries.

Figure 6 Predicting ratings in the G7 + China

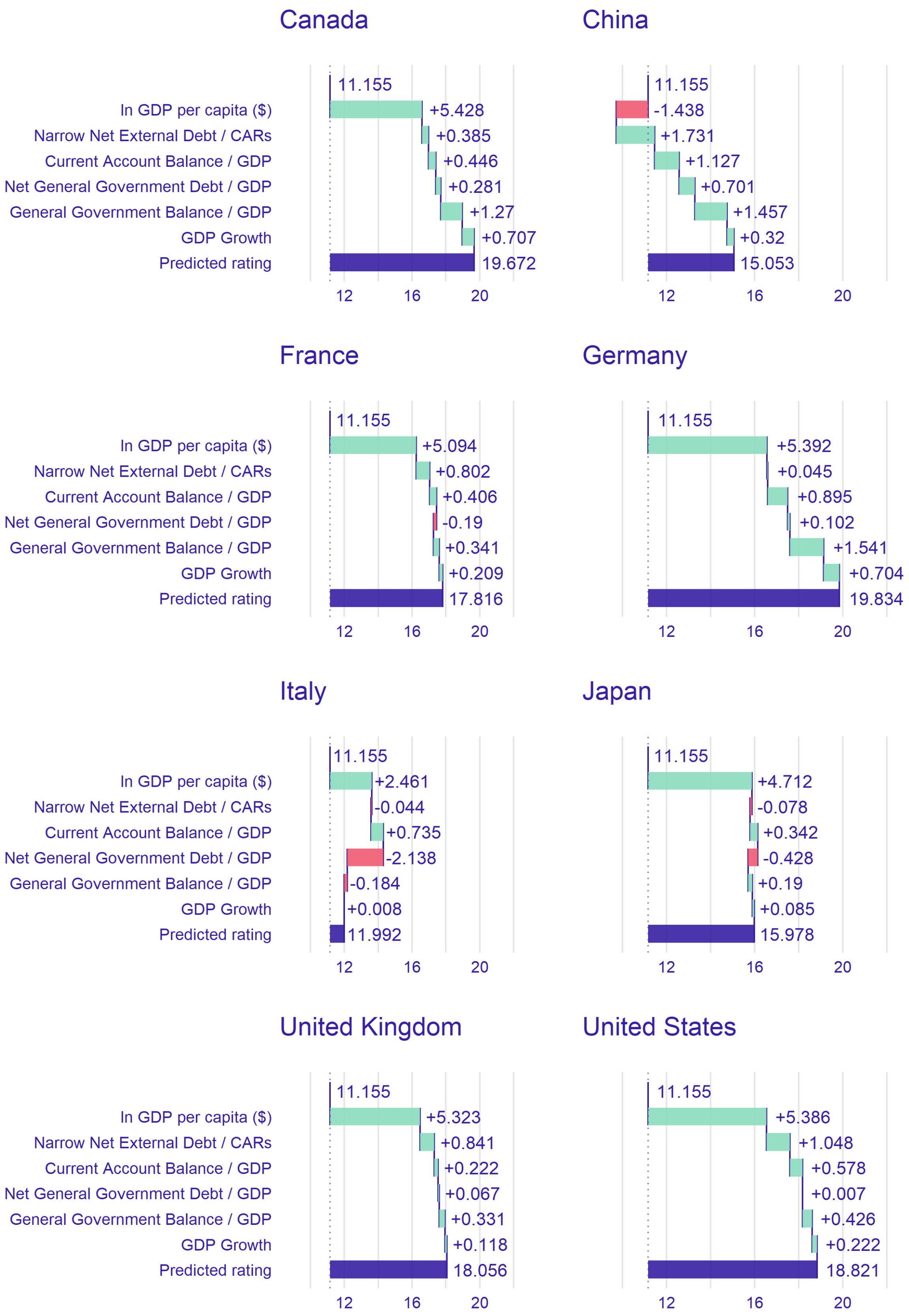

Figure 6 depicts how each variable affects the model's prediction of sovereign ratings for the G7 + China. In the absence of additional information, the initial best estimate of any sovereign's rating is simply the predicted sample average rating (11.155). Additional information shifts the predicted rating up or down. The direction and relative importance of each variable in predicting the rating varies across countries.

3. Empirical results

3.1. Step 1: Reconstructing ratings

Table 3 demonstrates our model's ability to predict existing sovereign ratings (i.e., before we incorporate climate change). Rows 2-5 indicate the deviation (in notches) between ratings issued by S&P and our predictions, starting with N=0 (exact match) to N=3 (our model is off by three notches). Columns 3-5 indicate increasingly restrictive slices of the data, starting with the whole sample in column 3, and providing results for out of sample tests (using 80% of the data to predict the remaining 20%) for all countries in column 4, and for only those countries with investment grade ratings in column 5.

Table 3 Predictive accuracy of our ratings prediction model

		Whole sample	**Out of sample 80/20% split**	**Investment grade only. Out of sample 80/20%**
% predicted within n notches	N = 0	68.01	34.26	45.45
	N = 1	96.43	79.63	87.27
	N = 2	99.84	94.44	94.55
	N = 3	-	98.15	-
Observations		644	536 / 108	270 / 55
Countries		109	109 / 108	60 / 55

Notes: Table 3 presents the results of the predictive capacity for our benchmark random forest model. Columns 3-5 show the percentage accuracy of our model corresponding to the number of notches in Column 2. Columns 3, 4 and 5 present the results for the whole sample, out of sample and investment grade only respectively. Data sample covers S&P ratings issued 2015-2020.

Our benchmark model (column 4) yields exact matches between predicted and observed ratings 34.26% of the time, increasing to over 90% accuracy within two notches. The literature indicates that eliminating countries that have recently defaulted can improve predictive accuracy. To test this, column 5 restricts the analysis to only those countries with investment grade ratings. Although we see a minor increase in exact matches, we see a loss of accuracy within two notches in out of sample tests. One potential reason is that focusing only on investment grade sovereigns reduces the sample for training the model by nearly half. A further concern is that vulnerability to climate change may be correlated with low sovereign ratings, for instance if developing countries rely more heavily on climate-sensitive industries such as agriculture, have less climate resilient infrastructure (e.g., poor road quality or flood defences), and have lower quality governance and institutions. Eliminating these countries from the sample would make our results less representative. As such, we include all 109 countries in the sample and is trained on S&P's ratings issued between 2015 and 2020.

Figure 7 presents graphical interpretations of the out-of-sample accuracy of sovereign rating predictions given in Table 3 (column 4). The solid line depicts perfect matches between estimated and observed ratings. Each observation is accompanied by the predicted rating (dot) and its error. Out-of-sample predictions yield exact matches for up to 34.26% of the data and are within 2 notches over 90% of the time. Standard errors are produced using the jackknife methodology summarised in Wager et al. (2014). The errors in this model are derived from the uncertainty in the random forest estimation. Each of the 2,000 trees we estimate in our random forest model produce an outcome. The size of whiskers for each observation in Figure 7 below depict the range of ratings predicted for that particular outcome in each tree. Figure 8 depicts the geographical spread of the model's out-of-sample accuracy. The key observation is that high predictive accuracy does not appear to be concentrated in any particular region, climate, size, development status, or political system. Exact matches appear for countries as diverse as Brazil, Finland, Uganda, Germany, Honduras, and Mongolia. Most of the G20 countries are predicted within one notch. Argentina, Colombia, Ecuador and Iraq are the least well predicted by our model, which may be expected due to the history of debt crises, defaults, civil unrest, war, and government instability in these countries. Because we do not have credible quantitative data on the effect of climate change on these governance indicators, they are not included in our ratings prediction model.

Figure 7 Out of sample accuracy of our ratings prediction model

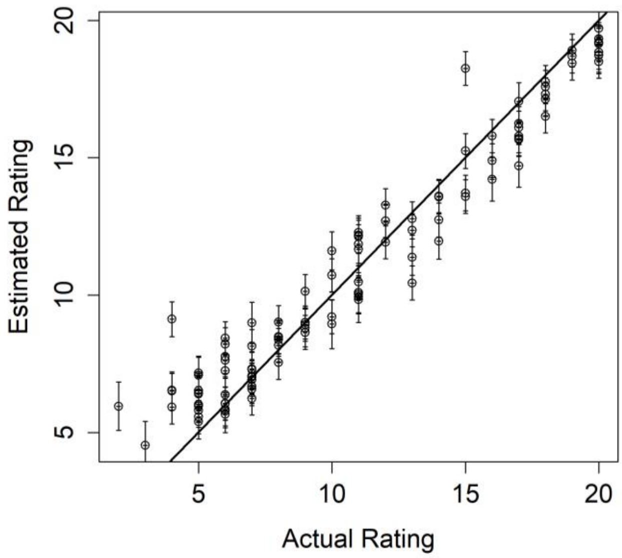

Figure 7 depicts out-of-sample predictive accuracy of our ratings prediction model. The thick black line represents a perfect match between the observed rating in 2020 (x-axis) and the model's prediction (y-axis). Error bars represent the range of ratings predicted for that outcome in each tree.

Figure 8 Out of sample predictive accuracy of our sovereign ratings model

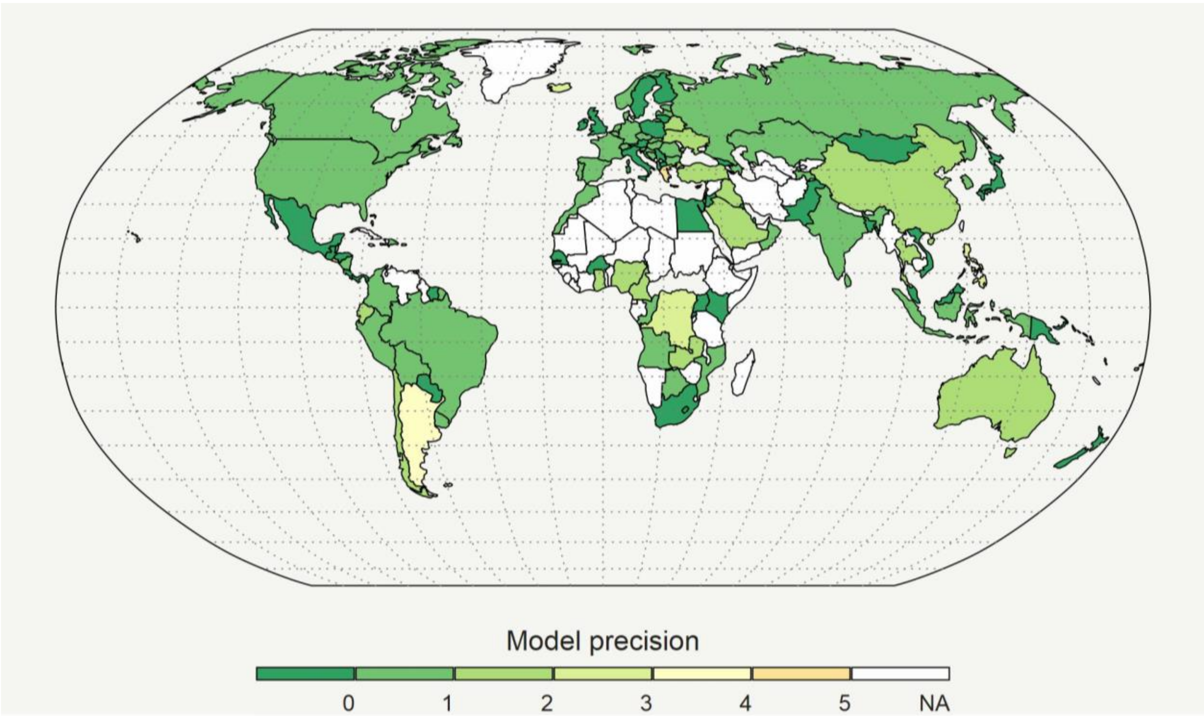

Figure 8 depicts out-of-sample predictive accuracy of our ratings prediction model. There is strong predictive accuracy across most of the world, including countries of varying size, latitude, coastal extent, political system, economic structure, and population. Some countries are not rated by S&P and so cannot be predicted.

3.2. Step 2 Adjusting input data for climate change

Step two in our process entails adjusting the macroeconomic input data used to train the ratings prediction model for future scenarios of climate change. We consider four scenarios in total: RCP 2.6, RCP 8.5, RCP 2.6 with increased temperature volatility, and RCP 8.5 with increased temperature volatility. Details on these scenarios are provided in Appendix A, but RCP 2.6 can broadly be considered consistent with the Paris Climate Agreement and limiting warming to 2C. RCP 8.5 is a high emissions, high warming scenario that broadly corresponds to warming of around 4.5C by 2100.

Country-specific climate-adjusted GDP and GDP growth rates are taken from Kahn et al. (2021), who develop a stochastic growth model that links deviations of country-specific climate variables (temperature and precipitation) from their historical norms to real output per capita growth. Using data between 1960 and 2014 and 174 countries, they find that persistent deviations of temperature from time-varying and country-specific historical thresholds (i.e., the historical norm) reduces per capita output growth, amounting to around 7% reduction in gross world product by 2100 in the absence of mitigation policies (with the global losses being significantly higher at 13% if the country-specific variability of climate conditions were to rise commensurate to temperature increases). We also report results using two alternative climate-economy models in Appendix C (Burke et al., 2015; Kalkuhl and Wenz 2020). Climate-adjusted GDP enters into our model in two ways: directly, as GDP and its growth rate comprise two of the six variables, and indirectly, as climate-adjusted GDP is used to adjust the four government balance variables.[13] To derive climate-adjusted government performance indicators, we extrapolate statistical models based on data from S&P (2015b). S&P produce estimates of the effect of various climate and natural disasters on our set of government balance indicators. For instance, using the scenario of a 1 in 250 – year earthquake, they estimate the damage caused, impacts on GDP per capita. They repeat this analysis for tropical cyclones,

[13] An alternative approach could entail training a random forest model on simulations of what ratings and macroeconomic indicators might look like in 2100, and to use that model to conduct counterfactual analyses of climate impacts. Instead, we train our model on 2015-2020 data and incorporate projections of climate-driven GDP losses from Kahn et al. (2021). We prefer our approach because (i) it enables us to train the ratings prediction model on observed rather than simulated data, and (ii) where simulations are required, they are required for 2 of 6 rather than 6 of 6 variables, and these are available in the peer-reviewed literature. In effect, this means we combine future GDP shortfalls with current ratings data and macroeconomic indicators, which we adjust for climate change as per Kahn et al. (2021), a suite of alternative climate economy models (see Appendix C), and S&P (2015a,b).

floods and winter storms. To make use of this data, we combine the tables in S&P (2015b) and assume homogeneity across the various events.

Figure 9 illustrates the process. Data points combine values from tables in S&P (2015b) describing the relationship between disaster-induced losses in per capita GDP and the log of each government performance indicator. To adjust these variables for climate change, we need a function describing the data in Figure 9. To derive this function, we first fit a linear model (red line), followed by polynomials of increasing order until ANOVA tests indicate no further significance is achieved. Using the coefficients from the best fit polynomial, we apply GDP losses determined by the climate-economy model to derive climate-adjusted indicators for each country.

Figure 9 Fitting models of the effect of GDP loss on government performance variables

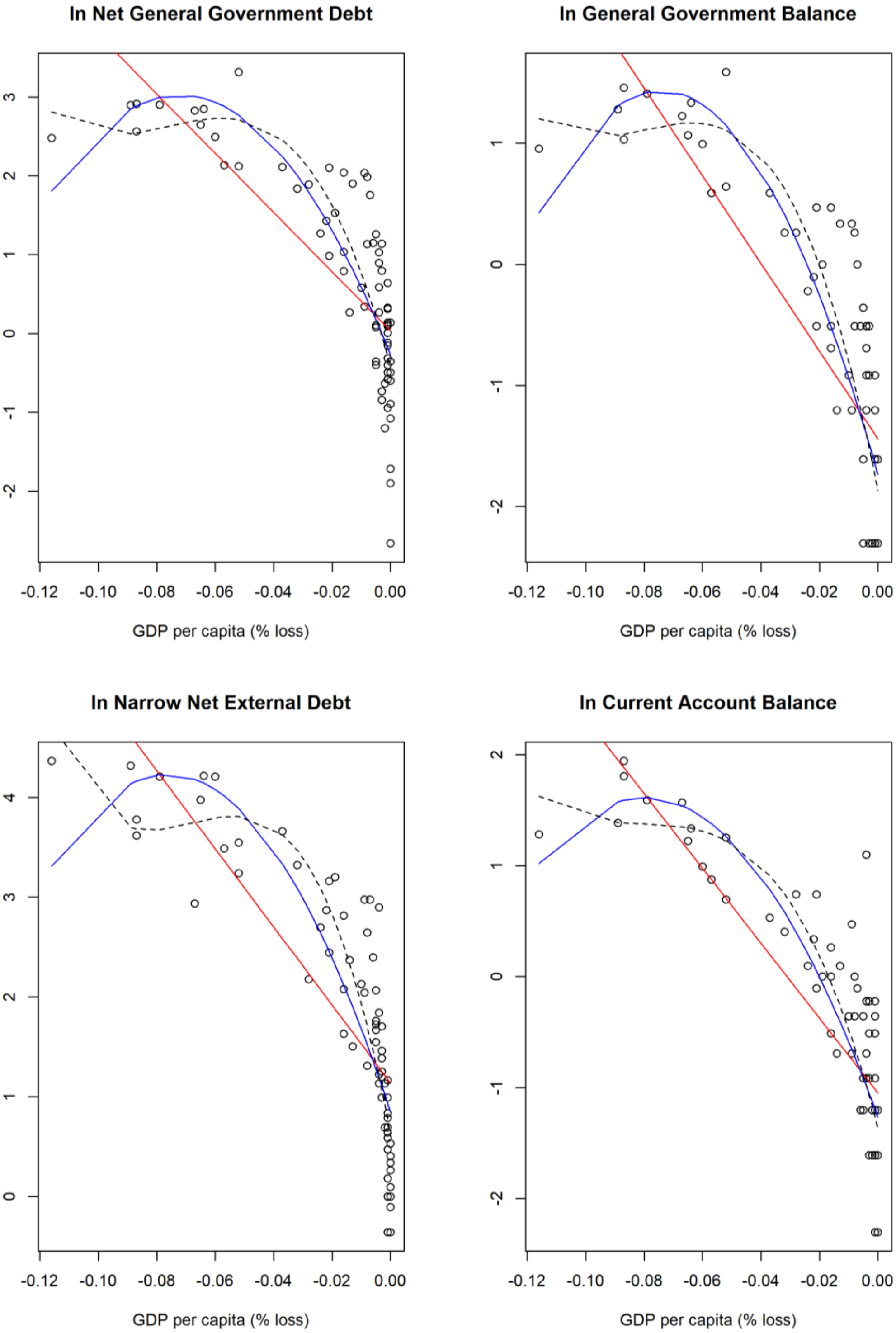

Figure 9 depicts the process for adjusting the government performance variables for future climate change. S&P's (2015) estimates of the spillover effects of natural disasters on per capita GDP onto other ratings factors are plotted (dots). To describe the distribution, polynomials of increasing order are fitted until no better fit can be found. These functions are then used to adjust each government performance indicator for the GDP losses under each warming scenario.

This approach is a simplification, as more sophisticated models of the effects of each type of disaster on GDP may be available. However, we believe this is justified for two reasons. First, in this step we are not interested in the effect of disasters on GDP, but rather the effect of the change in GDP on e.g. net general government debt. Our measure of the effect of climate on GDP comes directly from Kahn et al. (2021). Second, this approach provides practitioner evidence on the expected relationship between GDP losses and these macro indicators, keeping our approach as close as possible to real-world practice in CRAs. Finally, the approach enables us to continue to rely on the same direct links between climate science and climate economics that we use for adjusting GDP and its growth rate.

3.3. Step 3 Climate adjusted sovereign ratings: baseline model

We next present the results from our baseline model[14] under two warming scenarios (RCP 2.6 and RCP 8.5) for the years 2030, 2050, 2070, and 2100.[15] All results presented here rely on the same macroeconometric climate model from Kahn et al. (2021). Note that we present results using central estimates. Whilst it would be ideal to consider the full uncertainty space, we aim to replicate the applied methodologies of rating agencies as faithfully as possible.[16] This includes the treatment of risk and uncertainty. Any rating is by definition characterised by risk and uncertainty, because it opines on the likelihood of a hypothetical event in the future (a default on financial obligations). Rating agencies aim to assess those risks by applying a clearly defined methodology, which includes a substantial amount of discretion. After having weighed all the risks and uncertainties, however, the agencies will express their opinion through a single alphanumeric rating. No market-relevant agency would produce an output that fully reflects the variability of potential outcomes through, for example, a fan chart assessing various probabilities of rating outcomes. Specifically, when assessing the potential impact of climate change on sovereign creditworthiness, the result was expressed in a simple number of notches of rating changes, focusing exclusively on the base case of climate change estimates (S&P 2015a,b). For decades, markets have expected from agencies a simple, one-dimensional shorthand for default risk. Accordingly, this is exactly what the agencies deliver. We replicate this common practice in order to make our results more relevant and easily accessible for

[14] 109 countries, using ratings from 2015 to 2020, 6-variables, Kahn et al. (2021) for the climate-economy model.
[15] Figures for 2050, 2070, 2100 are available upon request.
[16] We believe we are well placed to comment on this, as one of our authors was S&P's Global Sovereign Chief Rating Officer and was co-author of the S&P (2015a,b) studies.

investors and regulators. Just as the rating agencies, we do not negate the uncertainty surrounding such point-estimates, but align our results with capital market practice.

Panels A and B of Figure 10 present simulated, climate-adjusted sovereign ratings under RCP 8.5 and RCP 2.6 for the year 2030 respectively. As in Figure 4, the horizontal axis indicates current ratings by S&P and the thick black line represents exact matches between current and predicted ratings. Here, however, our predicted ratings are inclusive of climate change under RCP 8.5, with the dotted line indicating best fit. The results indicate that climate-induced sovereign downgrades may be expected within the next decade and are most likely to impact the highest rated countries.

Figure 10 Climate-adjusted ratings: 2030 (RCP 8.5 versus RCP 2.6)

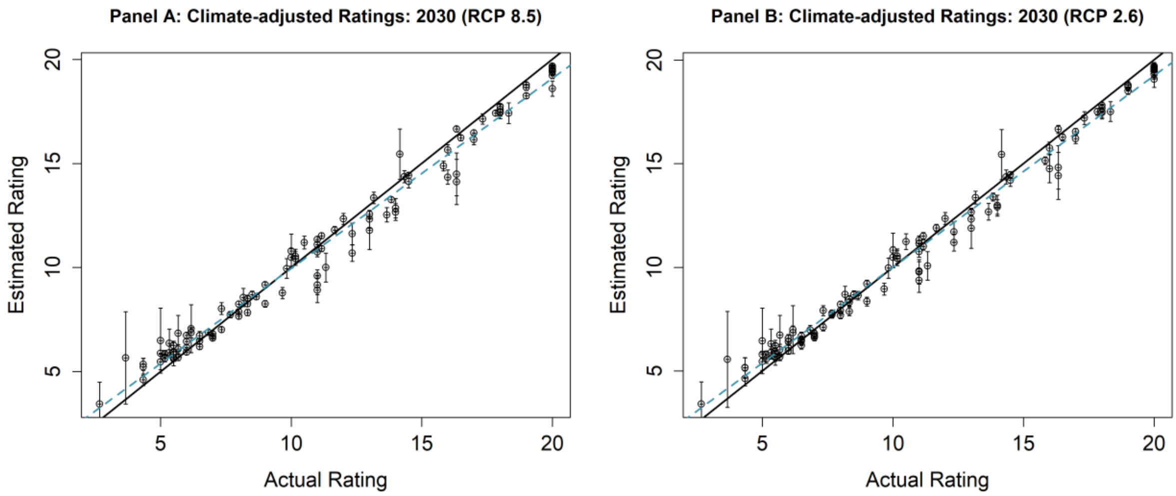

Figure 10 depicts climate-adjusted predicted ratings under RCP 8.5 (Panel A) and RCP 2.6 (Panel B) by 2030. The thick black line indicates there is no difference between the actual rating observed in 2020 (x-axis) and the predicted rating (y-axis). Under RCP 2.6, only minor downgrades can be expected and these are concentrated among the highest rated sovereigns. Under RCP 8.5, downgrades are far greater, observed along a greater range of ratings, but are still most pronounced at the top end of the rating scale. Standard errors are produced using the jackknife methodology summarised in Wager et al. (2014) and are derived from the uncertainty in the random forest estimation.

The concentration of downgrades at the top end of the ratings scale may appear counterintuitive, given that wealthier countries tend to have more diversified economies with greater capacity to respond to shocks. It may be expected that poorer countries (and therefore lower-rated sovereigns) are relatively more exposed and less able to respond to climate shocks. However, the underlying climate-economic model (Kahn et al., 2021) anticipates economic losses for countries at all development levels. For interpreting our results, it is important to remember that not all notches are created equal: a downgrade from AAA to AA+ reflects smaller reduction in creditworthiness than a downgrade from investment grade to speculative grade, or a rating downgrade within the range of speculative ratings. Ultimately, the nature of ratings changes is that top-rated sovereigns have further to fall and even small increases in default probability can trigger downgrades. At the lower end of the ratings scale, much larger increases in default probability are needed to drive downgrades. This nonlinear relationship between rating and default frequency is demonstrated by the agencies' annual rating default and transition studies (S&P 2020; Hadzi-Vaskov and Ricci, 2019). Moreover, our results demonstrate the effect of climate change on sovereign ratings, not on national economies. The fact that AAA rated countries may suffer worse downgrades than B rated ones does not imply that these wealthy countries will also suffer worse economic damages from climate change. Our result is consistent with the nature of sovereign ratings, which provide information about both the ability and willingness of sovereigns to service their debt. Countries with low ratings often already face a range of political, economic, and social challenges that indicate a low ability or willingness (or both) to service debt. Whilst we expect climate to have severe consequences for low-income countries, this may not further affect the rating if the country is already considered a high credit risk.

Finding downgrades just 10 years into the future is significant, as a common critique of the use of climate science in developing climate-finance metrics is that the timescales are incompatible: climate impacts accrue in the distant future, whereas financial decisions take place over a much shorter period. Our findings indicate that climate could impact ratings within the standard 10-year ratings horizon.

Figure 10, Panel B presents results for the same simulation under RCP 2.6. Although some downgrades are still predicted at the top end of the scale, these are fewer in number and intensity than under RCP 8.5. This demonstrates the potential for stringent climate policy to reduce the downward effect of climate change on sovereign ratings within the next decade.

Figure 11 presents the best fit lines for our climate-adjusted ratings under RCP 8.5 and 2.6, respectively, for 2030, 2050, 2070, and 2100 (Panels A and B). Axes and the bold lines are interpreted in the usual way. Data points indicate current observed and predicted ratings, excluding climate change. Figure 10, Panel A demonstrates climate-induced sovereign downgrades of increasing magnitude and across more countries as we look further into the future under RCP 8.5. Again, downgrades are largest at the top end of the ratings scale, but we begin to see impacts across the full range of investment grade sovereigns. In contrast, Panel B indicates that stringent climate policies consistent with RCP 2.6 continue to protect against substantial climate downgrades over the assessment period.[17] T-tests indicate that ratings predicted over any period to 2100 under RCP 2.6 are not statistically significantly different from each other or from current ratings predicted without climate change.

Figure 11 Climate-adjusted ratings to 2100 (RCP 8.5 versus 2.6)

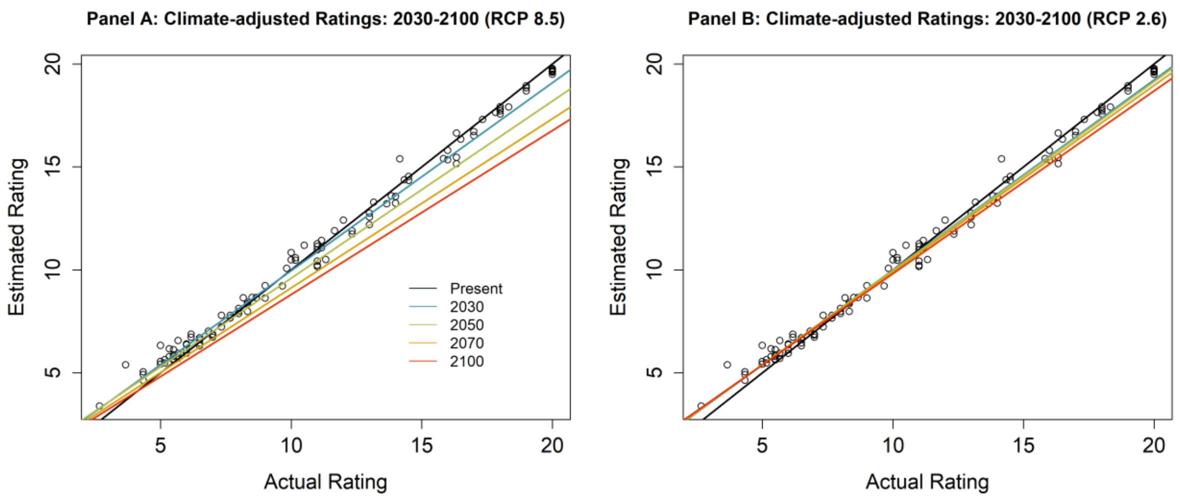

Figure 11 depicts climate-adjusted predicted ratings under RCP 8.5 (Panel A) and RCP 2.6 (Panel B) by 2030, 2050, 2070, and 2100. The thick black line indicates there is no difference between the actual rating observed in 2020 (x-axis) and the predicted rating (y-axis). Under RCP 2.6, only minor downgrades can be expected and these are concentrated among the highest rated sovereigns. Under RCP 8.5, downgrades are far greater, observed along a greater range of ratings, increase in intensity over time, but are still most pronounced at the top end of the rating scale.

Figures 12-13 depict the magnitude and geographical distribution of sovereign ratings changes predicted by our model by 2100 under RCP 2.6 and RCP 8.5, respectively. Under RCP 2.6, 58 sovereigns experience downward pressure on ratings by 2030, with an average reduction of 0.57 notches. The number of downgraded sovereigns increases marginally to 62 by 2100, with the intensity of the downgrade virtually unchanged when subjected to T-tests. Countries mostly affected by the downgrades are Chile and India with 7.11 and 3.73 notches respectively. Amongst other sovereigns we see Philippines, Indonesia and New Zealand in the range 2.29 to 3.60 notches. This suggests that limiting warming to well below 2°C could greatly reduce the effect of climate change on sovereign ratings.

[17] The tight bunching of best fit lines for 2030, 2050, 2070, and 2100 under RCP 2.6 around the bold line makes the time series difficult to discern graphically. T-tests confirm that they are not statistically significantly different from each other.

In contrast, under RCP 8.5, 59 sovereigns experience climate-induced downgrades by 2030, with an average reduction of 0.68 notches, rising to 81 sovereigns facing an average downgrade of 2.18 notches by 2100. The most affected nations include Chile, China, Slovakia, Malaysia, Mexico, India and Peru all exceeding 5 notches downgrades. The least affected by downgrades are Ukraine, Cyprus and Finland with results under 0.15 notches.

Figure 12 Global climate-induced sovereign ratings changes (2100, RCP 2.6)

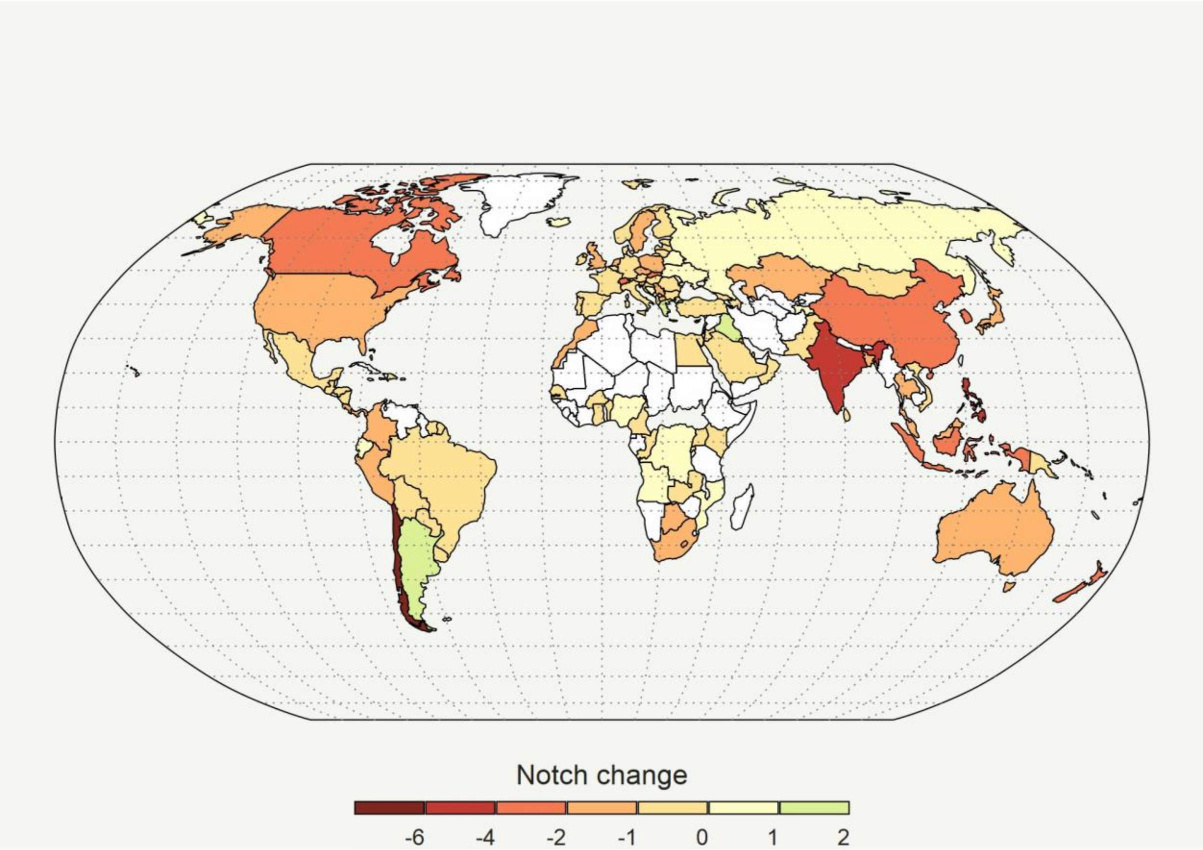

Figure 12 depicts climate-induced sovereign downgrades by 2100 under RCP 2.6. Under this scenario, 62 sovereigns face downgrades by 2100, with an average ratings loss of 0.94 notches on the 20-notch scale. Chile and India face the largest downgrades: 7.11 and 3.73 notches, respectively. Note that downward pressure on ratings is widespread across latitude, income level, economic structure, and political systems.

Figure 13 Global climate-induced sovereign ratings changes (2100, RCP 8.5)

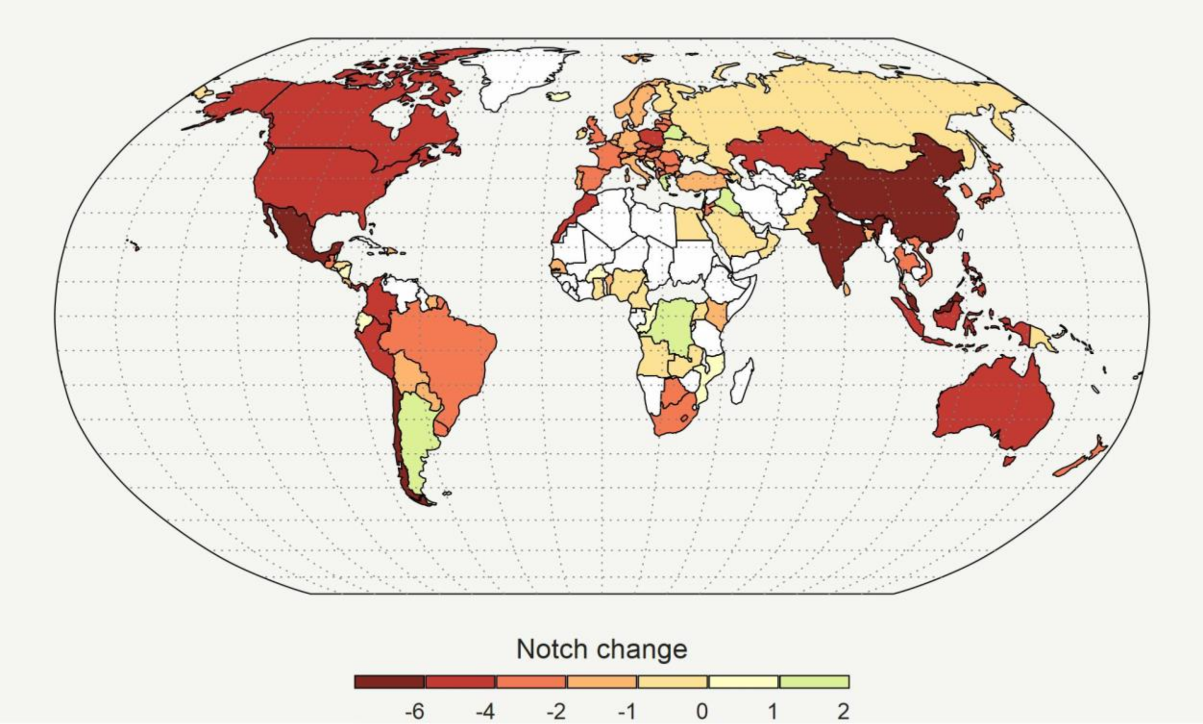

Figure 13 depicts climate-induced sovereign downgrades by 2100 under RCP 8.5. Under this scenario, 81 sovereigns face downgrades by 2100, with an average ratings loss of 2.18 notches on the 20-notch scale. Chile and China face the largest downgrades: 7.43 and 6.53 notches, respectively. Note that downward pressure on ratings is widespread across latitude, income level, economic structure, and political systems.

Combined, the maps indicate a now familiar story: stringent climate policy under RCP 2.6 and largely consistent with the Paris Climate Agreement is associated with only minor downgrades across most of the world.[18] In both figures, some countries – Argentina, Iraq, and Ecuador – appear to receive upgrades. This highlights an inconvenient limitation, driven by the lack of credible assessments of how climate change will affect political instability. Ultimately, what these results show is that based purely on the variables included in the model, we would expect these countries to have a higher rating than they do, and this holds true *even after* we incorporate climate-driven economic losses. 'Off-model,' we know why this is the case: ratings in these countries are driven by default history, war, and corruption – none of which are included in our model. This is why the out-of-sample tests indicate poor predictive accuracy for these economies (see Figure 8). The interpretation is not that climate change will improve

[18] Note that while this paper is a first attempt to bridge the gap between climate science and real-world financial indicators, considerable advances and investment in climate modelling, as well as in co-operation between the climate modelling and economic communities, are needed if we are to develop the capacity to understand the effects of climate change (including transition risks) more reliably on country-level economic output and at a more granular level. There is significant research potential in such collaborative work for both economics and science.

their ratings, but that in these countries off-model factors such as default history and political instability remain primary drivers of ratings.

3.4. Increased temperature variability

Our baseline model relies on Kahn et al. (2021) to describe the impacts of warming on real GDP and GDP growth rates. They explicitly model changes in the distribution of weather patterns; that is not only averages of climate variables that the climate-macro literature focuses on but also their variability. Therefore, this model enables us to incorporate varying degrees of temperature volatility within the overall warming trend. Put simply, we can choose whether warming is characterized by high and low temperatures that cluster tightly around their 30-year moving averages, or whether they deviate with increasing volatility as temperature rises. Lower volatility could reduce shocks and means adaptation costs can be spread over time. Higher volatility may require more upfront investments and lead to asset stranding. Beyond rises in the *average*, rises in the *volatility* of temperature are increasingly recognised as economically important. For instance, Kotz et al. (2021) find that increased temperature volatility reduces economic growth "independent of and in addition to changes in annual average temperature."

To incorporate the effects of increased temperature volatility in our model, we allow temperature increases to affect the variability of temperature shocks commensurately, or in other words we keep the coefficient of variation unchanged. Specifically, we generate a new set of input data describing a different climate scenario – one that entails not only warming temperatures, but also increasing temperature volatility – to feed into the same ratings prediction model described in Sections 2.3 and 3.1. On average, this new scenario increases the costs of climate change by 80% globally under RCP 8.5, with the size of these income effects varying across countries depending on the pace with which temperatures increase and historical variability of climate conditions in each country. Ultimately, the exercise demonstrates that the model can be readily extended to incorporate additional climate scenarios as scientific and economic evidence improves.

Compared to Panel B of Figure 11, Panel B of Figure 14 indicates that climate change will have a larger impact on sovereign ratings if temperature volatility rises, even under RCP 2.6. However, although the effect is marginally larger, it remains the case that stringent policies consistent with RCP 2.6 will limit the effect of climate on sovereign ratings. In contrast, Figure 14, Panel A demonstrates that increased temperature volatility leads to far more substantial climate-induced sovereign downgrades, sooner, and along a much wider range of the ratings scale. For further results see Appendix E.

Figure 14 Climate-adjusted ratings with increased temperature volatility (RCP 8.5 versus 2.6)

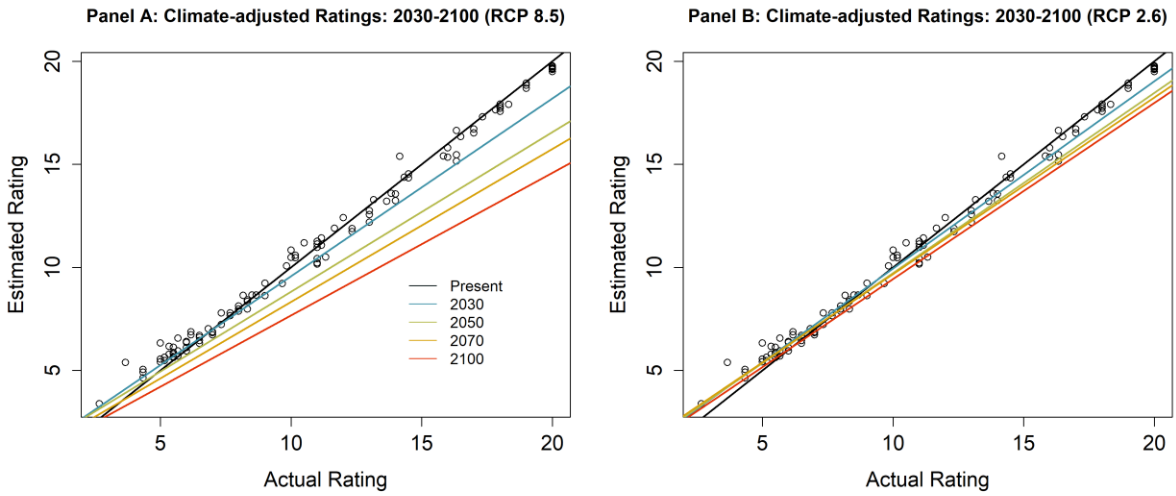

Figure 14 introduces rising temperature volatility into climate-adjusted predicted ratings under RCP 8.5 (Panel A) and RCP 2.6 (Panel B) by 2030, 2050, 2070, and 2100. The thick black line indicates there is no difference between the actual rating observed in 2020 (x-axis) and the predicted rating (y-axis). Compared to Figure 11, the same trends hold, but are exacerbated. For further results see Appendix E.

3.5 Alternative assumption on adaptation to climate change

In this section we present alternative results depending on the assumption relating to the speed at which countries adapt to global warming. Kahn et al. (2021) consider deviations in temperature and precipitation from their long-term moving averages. They produce results based on a 20-, 30- and 40-year long-term moving average. Our baseline results described in Section 3.3 are produced using the 30-year moving average. In this section we present our baseline model with the assumptions of a 20- and 40-year moving average. We consider this an appropriate test of the error bound within the underlying climate model. This way we can observe the variation in the estimates while changing the assumptions on the input.[19] Figure 15 and 16 below represent the results based on a 20 and 40 year moving average respectively.

[19] We would like to thank an anonymous reviewer for the suggestion of this robustness check.

Figure 15 Climate-adjusted ratings with a 20 year moving average temperature trend (RCP 8.5 versus 2.6)

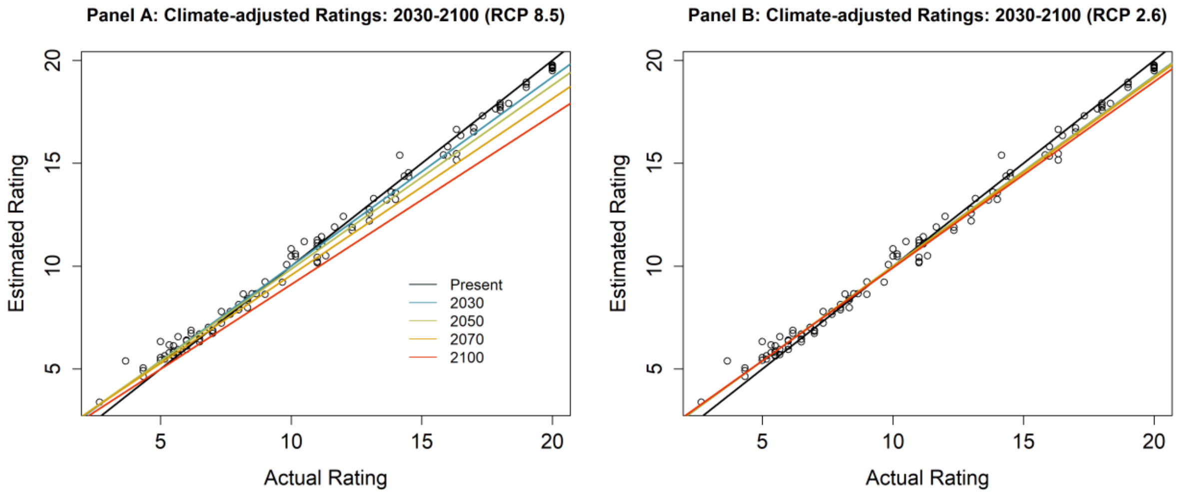

Figure 15 introduces a faster rate of climate adaptation (20-year moving average temperature trend) under RCP 8.5 (Panel A) and RCP 2.6 (Panel B) by 2030, 2050, 2070, and 2100. The thick black line indicates there is no difference between the actual rating observed in 2020 (x-axis) and the predicted rating (y-axis).

Figure 16 Climate-adjusted ratings with a 40 year moving average temperature trend (RCP 8.5 versus 2.6)

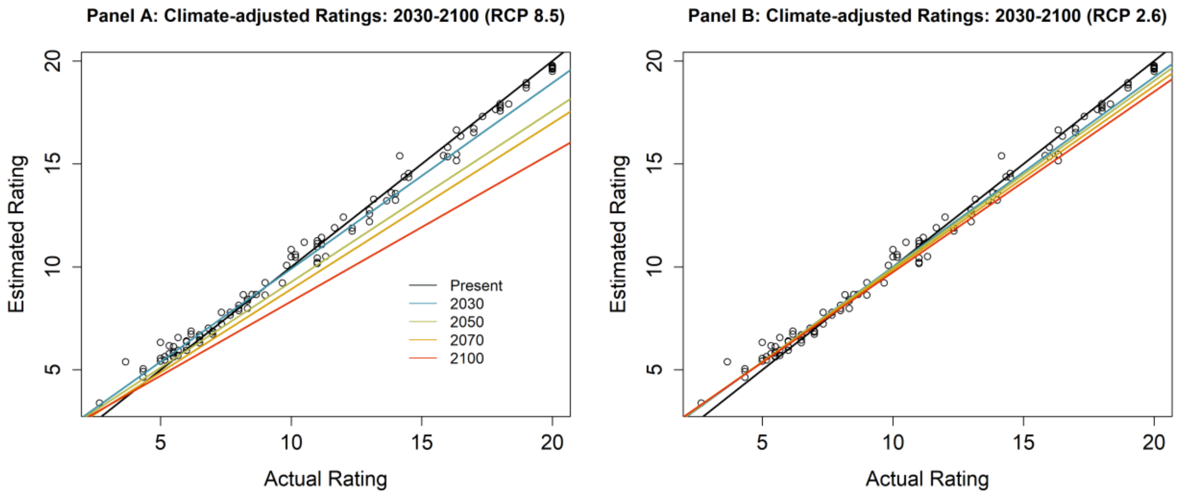

Figure 16 introduces a slower rate of climate adaptation (40-year moving average temperature trend) under RCP 8.5 (Panel A) and RCP 2.6 (Panel B) by 2030, 2050, 2070, and 2100. The thick black line indicates there is no difference between the actual rating observed in 2020 (x-axis) and the predicted rating (y-axis).

As expected we observe that the downgrades based on a 40-year moving average are more severe than the baseline 30-year moving average, and that these result are more severe still than the 20-year moving average. Table 4 presents the data in the above figures for the G7+China. We show the estimated ratings on a moving average 20-year, 30-year, 40-year and 30-year with additional temperature variability. Each of these outcomes are for the RCP 8.5 2100 scenario.

Table 4. Climate adjusted ratings to 2100 (RCP 8.5)

Country	Faster Adaptation	Baseline	Slower Adaptation	Increased Volatility
Canada	15.22	15.28	11.69	11.68
China	11.44	9.80	9.17	9.51
France	16.21	15.30	15.34	15.45
Germany	19.31	19.22	18.76	18.41
Italy	11.51	11.13	11.24	12.58
Japan	13.88	13.44	10.67	9.38
United Kingdom	16.21	14.88	14.43	14.73
United States	14.30	14.32	12.87	11.89

Notes: Table 4 shows the estimates sovereign credit ratings for the G7 + China in the RCP 8.5 (2100) scenario. Columns 2 to 5 show the estimated ratings for faster adaptation, baseline, slower adaptation and baseline with increased temperature variability respectively.

4. Additional cost of sovereign and corporate borrowing due to climate-induced sovereign downgrades

Previous research demonstrates that sovereign downgrades increase sovereign spreads (Afonso et al., 2012; Gande and Parsley 2005). Estimates of the effect of a 1-notch downgrade in sovereign rating on increases in yield spreads range from 0.08-0.112% (Afonso et al., 2012) to 0.12% (Gande and Parsley 2005). Taking these as lower and upper bounds (respectively) enables us to calculate ranges for the increase in annual interest payments on public debt due to climate-induced sovereign downgrades. Table 5 reports these costs for the G7 plus China under RCP 2.6 scenario by 2100. Columns 2-3 present climate-induced sovereign downgrades (in notches) and total outstanding sovereign debt as of 2019. Columns 4-5 report lower and upper bound estimates of the additional cost of sovereign debt due to climate downgrades. Climate-induced sovereign downgrades could increase the cost of sovereign debt across our sample by US$ 44.66 billion to US$ 66.99 billion under RCP 2.6. These costs are more than 3 times larger under RCP 8.5, with a lower-bound of US$ 135.24 billion and an upper-bound of US$ 202.86 billion (see Table 6).

Table 5. Additional cost of sovereign borrowing due to climate-induced sovereign downgrades (RCP 2.6, 2100)

Sovereign	**Sovereign downgrade (notches)**	**Outstanding sovereign debt ($ bn)**	**Cost of sovereign borrowing ($ bn) (lower bound)**	**Cost of sovereign borrowing ($ bn) (upper bound)**
Canada	1.84	557.10	0.82	1.23
China	1.80	2464.40	3.55	5.32
France	0.23	2026.10	0.37	0.56
Germany	0.48	1254.30	0.48	0.72
Japan	1.42	10396.20	11.81	17.72
United Kingdom	0.77	2710.70	1.67	2.50
United States	1.25	16673.40	16.67	25.01
G7 + China	1.11	36082.20	35.37	53.06
Full sample total	**0.92**	**44184.30**	**44.33**	**66.49**

Notes: Translating climate-induced sovereign downgrades into increased sovereign cost of borrowing by 2100 under RCP 2.6 scenario for G7 plus China. Italy is not downgraded under this scenario. Full sample results for 55 downgraded sovereigns available in Appendix D, Table D.1. Outstanding sovereign debt figures for 2019 obtained from S&P SRIs. Conversion between sovereign downgrades into yields for lower bound is based on Afonso et al. (2012) and for upper bound on Gande and Parsley (2005), whereby 1 notch sovereign downgrade increases sovereign bond spread by 0.08% and 0.12% respectively. Note that the increase in cost of debt at the lower and upper bound for the bottom row is taken as the sum of the lower and upper bound for each country, rather than calculated statically based on the mean downgrade and sum of outstanding debt.

Table 6. Additional cost of sovereign borrowing due to climate-induced sovereign downgrades (RCP 8.5, 2100)

Sovereign	**Sovereign downgrade (notches)**	**Outstanding sovereign debt ($ bn)**	**Cost of sovereign borrowing ($ bn) (lower bound)**	**Cost of sovereign borrowing ($ bn) (upper bound)**
Canada	4.72	557.10	2.10	3.16
China	6.53	2464.40	12.87	19.31
France	2.70	2026.10	4.38	6.56
Germany	0.78	1254.30	0.78	1.17
Italy	0.53	2225.30	0.94	1.42
Japan	2.56	10396.20	21.29	31.94
United Kingdom	3.46	2710.70	7.50	11.25
United States	4.68	16673.40	62.43	93.64
G7 + China	3.25	38307.50	112.29	168.45
Full sample total	**2.18**	**48678.10**	**135.24**	**202.86**

Notes: Translating climate-induced sovereign downgrades into increased sovereign cost of borrowing by 2100 under RCP 8.5 scenario for G7 plus China. Full sample results for 80 downgraded sovereigns available in Appendix D, Table D.2. Outstanding sovereign debt figures for 2019 obtained from S&P SRIs. Conversion between sovereign downgrades into yields for lower bound is based on Afonso et al. (2012) and for upper bound on Gande and Parsley (2005), whereby 1 notch sovereign downgrade increases sovereign bond spread by 0.08% and 0.12% respectively. Note that the increase in cost of debt at the lower and upper bound for the bottom row is taken as the sum of the lower and upper bound for each country, rather than calculated statically based on the mean downgrade and sum of outstanding debt.

Translating sovereign rating changes into impacts on corporate cost of capital is more challenging, as no such direct translation exists in the literature. However, Almeida et al. (2017) quantify a sovereign spillover effect from sovereign to corporate ratings, whereby a one percentage point increase in sovereign yields increases corporate yields by a factor of 0.6-0.7. We follow a three-step procedure to calculate the effect of climate-induced sovereign ratings on the cost of corporate capital (see Tables 7 and 8 for RCP 2.6 and 8.5 respectively).[20] First, we translate sovereign downgrades into sovereign yield spreads as described above and reported in Tables 5-6. Second, we multiply these values (0.08% versus 0.12%) by the magnitude of the spillover effect from sovereign to corporate yields identified in Almeida et al. (2017), treating 0.6 (0.7) as the lower (upper) bound.[21] Finally, we calculate the resulting

[20] As before in these tables we report G7 countries plus China but results for the full sample are available in Appendix D, Tables D.1.-D.4.

[21] Authors estimate the effect around the investment versus speculative grade threshold. These results are for illustrative purposes only and should be considered with caution. We realise taking this measure and applying it to all corporate debt held by a sovereign is conservative since not all firms will be rated around that threshold.

costs of outstanding corporate debt in all countries in which we have data. Using data from the Bank of International Settlements (BIS), Table 7, column 3 reports outstanding corporate debt in US$ billion for the G7 + China as of June 2020. The availability of BIS data on corporate debt restricts our calculations to a sub-sample of 28 (34) countries under RCP 2.6 (8.5).

Lower- and upper-bound estimates of increases in the cost of corporate debt due to climate-induced sovereign downgrades are reported in columns 4-5. Under RCP 2.6, the lower (upper) bound estimates of the additional annual interest payments due to spillover of sovereign downgrades onto corporations will reach US$ 9.90 (17.33) billion by 2100 across all 28 sovereigns for which BIS data is available. It is worth noting that this is the indirect effect of increased sovereign credit risk induced by climate change and passed onto corporates. These costs can be considered in addition to the direct effects of climate change on corporates (e.g., physical, transition, and litigation losses). The magnitude of the sovereign downgrades increases corporate interest outlays significantly (almost 4 times) under the RCP 8.5 scenario and exceeds 34.94 (61.15) $ billion for lower (upper) bound, respectively.

Table 7. Additional cost of corporate debt due to climate-induced sovereign downgrades (RCP 2.6, 2100)

Sovereign	**Sovereign downgrade (notches)**	**Outstanding corporate debt ($ bn)**	**Increase in cost of debt ($ bn) lower bound**	**Increase in cost of debt ($ bn) upper bound**
Canada	1.84	515	0.45	0.80
China	1.80	4061	3.51	6.14
France	0.23	777	0.09	0.15
Germany	0.48	241	0.06	0.10
Japan	1.42	845	0.58	1.01
United Kingdom	0.77	564	0.21	0.36
United States	1.25	7126	4.28	7.48
G7 + China	1.11	14129	9.18	16.04
Total BIS	**1.03**	**15531**	**9.85**	**17.23**

Notes: Translating climate-induced sovereign downgrades into increased corporate cost of debt by 2100 under RCP 2.6 scenario. G7 plus China results presented here. Italy is not presented as it is not downgraded under this scenario. Data availability from BIS on corporate debt restricts our sample to 28 countries. Sub-sample results for the remaining 21 sovereigns calculated using BIS database available in Appendix D, Table D.3. To calculate the value of corporate debt affected by sovereign downgrades we first convert the sovereign rating changes into sovereign yield which we then convert into corporate sovereign yield. To translate sovereign ratings into yields we use lower bond (0.08%) from Afonso et al. (2012) and higher bound (0.12%) from Gande and Parsley (2005). To then convert these into corporate spreads we use Almeida et al. (2017)' conversions, with 0.6 for lower bound and 0.7 for higher bound. We multiply sovereign rating changes (see column 2) by an amount of outstanding debt at end-June 2020 (column 3) and 0.00048 for a lower bound (0.08%*0.6) and 0.00084 (0.12%*0.7) for a upper bound respectively. Note that the increase in cost of debt at the lower and upper bound for the bottom row is taken as the sum of the lower and upper bound for each country, rather than calculated statically based on the mean downgrade and sum of outstanding debt.

Table 8 Additional cost of corporate debt due to climate-induced sovereign downgrades (RCP 8.5, 2100)

Sovereign	Sovereign downgrade (notches)	Outstanding corporate debt ($ bn)	Increase in cost of debt ($ bn) lower bound	Increase in cost of debt ($ bn) higher bound
Canada	4.72	515	1.17	2.04
China	6.53	4061	12.73	22.28
France	2.70	777	1.01	1.76
Germany	0.78	241	0.09	0.16
Italy	0.53	152	0.04	0.07
Japan	2.56	845	1.04	1.82
United Kingdom	3.46	564	0.94	1.64
United States	4.68	7126	16.01	28.01
G7 + China	3.25	14281	33.03	57.78
Total BIS	**2.66**	**15699**	**34.94**	**61.15**

Notes: Translating climate-induced sovereign downgrades into increased corporate cost of debt by 2100 under RCP 8.5 scenario. G7 plus China results presented here. Data availability from BIS on corporate debt restricts our sample to 34 countries. Sub-sample results for the remaining 26 sovereigns calculated using BIS database available in Appendix D, Table D.4. To calculate the value of corporate debt affected by sovereign downgrades we first convert the sovereign rating changes into sovereign yield which we then convert into corporate sovereign yield. To translate sovereign ratings into yields we use lower bond (0.08%) from Afonso et al. (2012) and higher bound (0.12%) from Gande and Parsley (2005). To then convert these into corporate spreads we use Almeida et al. (2017)' conversions, with 0.6 for lower bound and 0.7 for higher bound. We multiply sovereign rating changes (see column 2) by an amount of outstanding debt at end-June 2020 (column 3) and 0.00048 for a lower bound (0.08%*0.6) and 0.00084 (0.12%*0.7) for a higher bound respectively. Note that the increase in cost of debt at the lower and upper bound for the bottom row is taken as the sum of the lower and upper bound for each country, rather than calculated statically based on the mean downgrade and sum of outstanding debt.

The above calculations show that impacts of climate-induced sovereign downgrades on debt servicing costs are large in magnitude for both sovereigns and corporates. With maturities of debt products extending[22] and meaningful economic implications of climate change drawing nearer, investors will progressively need more reliable credit opinions beyond the relatively short-term 5-10 years horizon[23] offered by CRAs today. This research has set the foundations for such a longer-term view. Based on the methodology applied here, future research could focus on the development of ultra-long ratings that investors could consider when assessing long-dated sovereign credit exposures. Currently CRAs apply the same "long-term" rating to a 2-year bond as they do to a 50-year or century-bond. This equalisation of risk is clearly implausible. A transparent and scientifically grounded truly long-term rating will help support

[22] For instance, governments issue ever-longer dated bonds as long as 100 years (e.g., Argentina, Austria, Belgium, Ireland).

[23] CRAs issue what they refer to as "long-term" ratings but the time horizon extends to no more than 5-10 years, which is a fraction of the length of some of the bonds now being sold, and a relatively short period compared to the process of climate change.

better investment decisions today, expose stranded assets earlier and create incentives for public policies and investments that contribute to containing and mitigating climate change. Such an instrument would therefore promote the global public good of climate protection and diminish the market failure that has created the climate crisis in the first place. Truly long-term credit views can help make climate risks visible within mainstream financial indicators, thus supporting investors to take decisions that are environmentally and financially sustainable for the long haul (Griffith-Jones and Kraemer 2021; Spiegel et al., 2022).[24,25]

Our research has strong policy implications for CRAs' regulators including ESMA and SEC. Significant changes due to climate change and aging societies are inevitable and sovereign credit ratings are not designed to reflect those ultra-long-term risks. Additionally, the "up to ten-year" horizon that CRAs pursue is not credible. Credit reports on sovereigns will include forecasts that typically only reach three years into the future, at most, and exceptionally to five. Regulators could therefore insist that CRAs document how they fulfil their current claim of a 5 to 10-year time horizon. In a second step regulators should require CRAs to demonstrate how they intend to incorporate long-term challenges such as demographic or climate change. Regulators must begin to look at more fundamental credit issues that could over a longer period impact the functioning of the capital market and its stability.

5. Concluding remarks

This research contributes to bridging the gap between climate science and real-world financial indicators. Combining climate science with economics, machine learning, and practitioner expertise, we simulate the effect of climate change on sovereign creditworthiness, producing the world's first climate-adjusted sovereign credit rating. The analysis is conducted using three distinct climate-economy models and yields qualitatively similar results under various warming scenarios. We document three key empirical findings. In contrast to much of the climate-economics literature, we find material impacts of climate change as early as 2030, with significantly deeper downgrades across more sovereigns as climate warms and temperature

[24] This will alleviate concerns raised by many in relation to climate service providers who "operate outside of the bounds of scientific merit" (Keenan 2019) and misuse climate models (Nissan et al., 2019).

[25] One important concern is whether predicting climate-induced downgrades in the future may increase the cost of debt today. This is particularly concerning for low-income countries where evidence suggests that climate-related natural disasters are already hitting bond yields (Beirne et al., 2020; Buhr et al., 2018; Kling et al., 2018). If investors believed that e.g., India is not a climate-safe investment, the perverse result could be to starve India of the access to capital it needs to increase resilience.

volatility rises. Under RCP 8.5, the average sovereign downgrade could reach 2.48 notches, with several countries falling 5 notches or more on a 20-notch scale. Second, our findings suggest that stringent climate policy consistent with the Paris Agreement will result in minimal changes to sovereign creditworthiness. Finally, from policy perspective, our results support the idea that deferring green investments will increase costs of borrowing for sovereigns, which in line with the existing literature will translate into higher costs of corporate debt. The additional costs to sovereigns in our sample range from US$ 45 to 67 billion under RCP 2.6, and US$ 135 to 203 billion under RCP 8.5. Corporates will experience additional costs of between US$ 10 and 17 billion under RCP 2.6, and between US$ 35 and 61 billion under RCP 8.5.

Perhaps most importantly, our approach demonstrates that it is possible to 'do ESG' without compromising scientific credibility. We show that existing climate science and economics are capable of supporting credible, decision-ready green finance indicators.

Future research should consider alternative ways of conceptualising this problem. Predictions may also be established by focusing on the hazard rate for default and the relationship this may have with GDP losses. This may prove to be a more complex task as downgrades may historically be more closely associated with non-linear jumps in GDP losses as opposed to the steady declines (year to year) produced by climate models.

This research is of interest to investors, sovereigns and CRAs alike. Governments issue ever-longer dated bonds, of which life insurance companies and pension funds are eager buyers, thus enabling them to match their own long-term liabilities. Therefore, investors should consider the long-term creditworthiness of sovereign issuers. Currently there is no reliable yardstick for assessing sovereign creditworthiness beyond the current decade and this research fills this gap. Our study offers a first methodological approach to extend the long-term rating to an ultra-long-term reality. Based on the methodology applied here future research could focus on developing ultra-long ratings not only for sovereigns but also for other issuers including corporates.

References

Adelino M, Ferreira MA (2016) Bank ratings and lending supply: Evidence from sovereign downgrades. *Review of Financial Studies*. 29:1709–1746.

Afonso A, Furceri D, Gomes P (2012) Sovereign credit ratings and financial markets linkages: Application to European data. *Journal of International Money & Finance*. 31:606–638.

Afonso A, Gomes P, Rother P (2009) Ordered response models for sovereign debt ratings. *Applied Economics Letters.* 16:769–773.

Agarwala M, Burke M, Klusak P, Mohaddes K, Volz U, Zenghelis D (2021) Climate change and fiscal sustainability: Risks and opportunities. *National Institute Economic Review.* 258:28–46.

Almeida H, Cunha I, Ferreira MA, Restrepo F (2017) The real effects of credit ratings: The sovereign ceiling channel. *Journal of Finance*. 72:249–290.

Auffhammer M (2018) Quantifying economic damages from climate change. *Journal of Economic Perspectives.* 32:33–52.

Augustin P, Boustanifar H, Breckenfelder J, Schnitzler J (2018) Sovereign to corporate risk spillovers. *Journal of Money, Credit & Banking*. 50:857–891.

Baghai RP, Servae H, Tamayo A (2014) Have rating agencies become more conservative? Implications for capital structure and debt pricing. *Journal of Finance*. 69:1961–2005.

Bastien-Olvera BA, Moore FC (2020) Use and non-use value of nature and the social cost of carbon. *Nature Sustainability*. 4:101–108.

Battiston, S, Monasterolo I (2019) A climate risk assessment of sovereign bonds' portfolio. SSRN Electronic Journal, 1, 1.

Baum CF, Schäfer D, Stephan A (2016) Credit rating agency downgrades and the Eurozone sovereign debt crises. *Journal of Financial Stability.* 24:117–131.

Beirne J, Renzhi N, Volz U (2021) Feeling the heat: Climate risks and the cost of sovereign borrowing. *International Review of Economics & Finance*. 76: 920–936.

Bennell JA, Crabbe D, Thomas S, ap Gwilym O (2006) Modelling sovereign credit ratings: Neural networks versus ordered probit. *Expert Systems with Applications*. 30:415–425.

Berg F, K¨olbel J, Rigobon R (2019) Aggregate confusion: The divergence of ESG ratings. Forthcoming *Review of Finance*.

Bloomberg Green (2021) The boom in ESG shows no signs of slowing. February 10, 2021.

Borensztein E, Cowan K, Valenzuela P (2013) Sovereign ceiling lite? The impact of sovereign ratings on corporate ratings in emerging market economies. *Journal of Banking & Finance.* 37:4014–4024.

Breiman L (2001) Random forests. *Machine Learning*. 45:5–32.

Brooks R, Faff RW, Hillier D, Hillier J (2004) The national market impact of sovereign rating changes. *Journal of Banking & Finance.* 28:233–250.

Buhr B, Volz U, Donovan C, Kling G, Murinde V, Pullin NLY (2018) Climate change and the cost of capital in developing countries. Assessing the impact of climate risks on sovereign borrowing costs. Imperial College Business School May 2018.

Burke M, Hsiang SM, Miguel E (2015) Global non-linear effect of temperature on economic production. *Nature*. 527:235–239.

Cantor R, Packer F (1996) Determinants and impact of sovereign credit ratings. *Economic Policy Review.* 2(2).

Capelle-Blancard G, Crifo P, Diaye M, Scholtens B, Oueghlissi R (2017) Environmental, social and governance (ESG) performance and sovereign bond spreads: An empirical analysis of OECD countries. Working paper, SSRN 2874262.

Chen SS, Chen HY, Chang CC, Yang SL (2016) The relation between sovereign credit rating revisions and economic growth. *Journal of Banking & Finance*. 64:90–100.

Chen C, Liaw A, Breiman L (2004) Using random forest to learn imbalanced data. 110:1–12. https://statistics.berkeley.edu/tech-reports/666

Cevik S, Jalles JT (2022a) An apocalypse foretold: Climate shocks and sovereign defaults. *Open Economies Review*. 33:89 –108.

Cevik S, Jalles JT (2022b) This changes everything: Climate shocks and sovereign bonds. *Energy Economics*. 107:105856.

Cevik S, Jalles JT (2020) Feeling the heat: Climate shocks and credit ratings. Working paper, IMF 2020/286.

Cornaggia JN, Cornaggia KJ, Hund JE (2017) Credit ratings across asset classes: A long-term perspective. *Review of Finance*. 21:465–509.

Correa R, Lee K, Sapriza H, Suarez G (2014) Sovereign credit risk, banks' government support, and bank stock returns around the world. *Journal of Money, Credit and Banking*. 46:93–121.

Crifo P, Diaye M, Oueghlissi R (2015) Measuring the effect of government ESG performance on sovereign borrowing cost. Working paper, Hal Departement D'economie Route de Saclay hal-00951304.

Dell M, Jones BF, Olken BA (2014) What do we learn from the weather? The new climate- economy literature. *Journal of Economic Literature*. 52:740–798.

Dell M, Jones BF, Olken BA (2012) Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal*: *Macroeconomics*. 4:66–95.

Deutsche Bundesbank (2019) Climate change and central banks.

Diaz D, Moore F (2017) Quantifying the economic risks of climate change. *Nature Climate Change*. 7:774–782.

Dietz S, Bowen A, Dixon C, Gradwell P (2016) "Climate value at risk" of global financial assets. *Nature Climate Change*. 6:676–679.

Dietz S, Stern N (2015) Endogenous growth, convexity of damage and climate risk: How Nordhaus' framework supports deep cuts in carbon emissions. *Economic Journal*. 125: 574–620.

De Moor L, Luitel P, Sercu P, Vanpée R (2018) Subjectivity in sovereign credit ratings. *Journal of Banking & Finance*. 88:366–392.

ESMA (2019) ESMA advises on credit rating sustainability issues and sets disclosure requirements, Press Release. July 18, 2019.

Fiedler T, Pitman AJ, Mackenzie K, Wood N, Jakob C, Perkins-Kirkpatrick SE (2021). Business risk and the emergence of climate analytics. Perspective. *Nature Climate Change*.

Fioramanti M (2008) Predicting sovereign debt crises using artificial neural networks: A comparative approach. *Journal of Financial Stability*. 4:149–164.

Fitch (2020) Fitch downgrades four Italian banks following sovereign downgrade. Published Tue 12 May 2020. Accessed April 10th 2022. https://www.fitchratings.com/research/structured-finance/covered-bonds/fitch-downgrades-four-italian-banks-following-sovereign-downgrade-12-05-2020

Fuchs A, Gehring K, Conrad C, Cordes T, Dovern J, Dreher A, Egger P, Forquesato P, Kauffeldt TF, Klasen S, Menkhoff L, Pinto P, Sch C (2017) The home bias in sovereign ratings. *Journal of the European Economic Association*. 15:1386–1423.

Gande A, Parsley DC (2005) News spillovers in the sovereign debt market. *Journal of Financial Economics*. 75:691–734.

Gennaioli N, Martin A, Rossi S (2014) Sovereign default, domestic banks, and financial institutions. *Journal of Finance*. 69:819–866.

Griffith-Jones S, Kraemer M (2021) Credit rating agencies and developing economies. DESA Working Paper No 175. ST/ESA/2021/DWP/175. December 2021. United Nations Department of Economic and Social Affairs.

Hadzi-Vaskov M, Ricci L (2019) The nonlinear relationship between public debt and sovereign credit ratings. IMF Working Papers, 19(162).

Hastie T, Tibshirani R, Friedman J (2009) The elements of statistical learning. Springer-Verlag New York.

Hausfather Z, Peters GP (2020) Emissions - the "business as usual" story is misleading. *Nature*. 577: 618–620.

Hepburn C, O'Callaghan B, Stern N, Stiglitz J, Zenghelis D (2020) Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change? Oxford Review of Economic Policy.
Howard-Grenville J (2021) ESG impact is hard to measure — but it's not impossible. Harvard Business Review.
Kahn ME, Mohaddes K, Ng RNC, Pesaran MH, Raissi M, Yang J-C (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*. 104:105624.
Kalkuhl M, Wenz L (2020) The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*. 103: 102360.
Kaminsky G, Schmukler SL (2002) Emerging market instability: Do sovereign ratings affect country risk and stock returns? *World Bank Economic Review*. 16:171–195.
Keenan JM (2019) A climate intelligence arms race in financial markets. *Science*. 365:1240–1243.
Kling G, Volz U, Murinde V, Ayas S (2021) The impact of climate vulnerability on firms' cost of capital and access to finance. *World Development* 137:105131.
Kling G, Lo YC, Murinde V, Volz U (2018) Climate vulnerability and the cost of debt. Working paper, SSRN 3198093.
Kotz M, Wenz L, Stechemesser A, Kalkuhl M, Levermann A (2021) Day-to-day temperature variability reduces economic growth. *Nature Climate Change*.
Li J, Mirza N, Rahat B, Xiong D (2020) Technological forecasting & social change machine learning and credit ratings prediction in the age of fourth industrial revolution. *Technological Forecasting & Social Change*. 161:120309.
Markellos R, Psychoyios D, Schneider F (2016) Sovereign debt markets in light of the shadow economy. *European Journal of Operational Research*. 252:220–231.
Mathiesen K (2018) Rating climate risks to credit worthiness. *Nature Climate Change*. 8:454–456.
Monasterolo I (2020) Climate change and the financial system. *Annual Review of Resource Economics*.12:299–320.
Moody's (2020) Rating action: Moody's has taken rating actions on 58 sub-sovereign entities after UK's sovereign action. Published: 21 Oct 2020. Accessed: April 10, 2022. Available at: https://www.moodys.com/research/Moodys-has-taken-rating-actions-on-58-sub-sovereign-entities--PR_434579
Moss R, Edmonds J, Hibbard K, Manning M, Rose S, van Vuuren D, Carter T, Emori S, Kainuma M, Kram T, Meehl G, Mitchell J, Nakicenovic N, Riahi K, Smith S, Stouffer R, Thomson A, Weyant J, Wilbanks T (2010) The next generation of scenarios for climate change research and assessment. *Nature*. 463:747–756.
Nissan H, Goddard L, de Perez EC, Furlow J, Baethgen W, Thomson MC, Mason SJ (2019) On the use and misuse of climate change projections in international development. *Wiley Interdisciplinary Reviews: Climate Change*. 10(d579).
Nordhaus WD, Boyer J (2000) Warming the world: Economic models of global warming. Cambridge, MA: The MIT Press.
Ozturk H, Namli E, Erdal H (2016) Modelling sovereign credit ratings: The accuracy of models in a heterogeneous sample. *Economic Modelling*. 54:469–478.
Painter M (2020) An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*. 135:468–482.
Pindyck RS (2013) Climate change policy: What do the models tell us? *Journal of Economic Literature*. 51:860–872.
PRI (2019) A practical guide to ESG integration in sovereign debt.
Ricke K, Drouet L, Caldeira K, Tavoni M (2018) Country-level social cost of carbon. *Nature Climate Change*.
S&P (2020) Default, transition, and recovery: 2020 annual sovereign default and rating transition study. April 12, 2021.
S&P (2018) How Environmental, social, and governance factors help shape the ratings on governments, insurers, and financial institutions. October 23, 2018.
S&P (2017) Sovereign rating methodology. December 18, 2017.
S&P (2015a) The heat is on: How climate change can impact sovereign ratings. November 25, 2015.

S&P (2015b) Storm Alert: Natural disasters can damage sovereign creditworthiness. September 10, 2015.
Siew RYJ (2015) A review of corporate sustainability reporting tools (SRTs). *Journal of Environmental Management.* 164:180–95.
Spiegel S, Chowla P, Ng PL, Erfurth P (2022) Credit rating agencies and sovereign Debt: Four proposals to support achievement of the SDGs. UN DESA Policy Brief No 131.
Stern N (2008) The economics of climate change. *American Economic Review*. 98:1–37.
TCFD (2020) Task force on climate-related financial disclosures: 2020 status report. Financial Stability Board.
TCFD (2017) Recommendations of the task force on climate-related financial disclosures. Financial Stability Board.
Van Gestel T, Martens D, Baesens B, Faremans D, Huysmans J, Vanthienen J (2007) Forecasting and analyzing insurance companies' ratings. *International Journal of Forecasting*. 23:513–529.
Van Gestel T, Baesens B, Van Dijcke P, Garcia J, Suykens AKJ, Vanthienen J (2006) A process model to develop an internal rating system: sovereign credit ratings. *Decision Support Systems*. 42:1131–1151.
Van Vuuren D, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, Hurtt G, Kram T, Krey V, Lamarque JF, Masui T, Meinshausen M, Nakicenovic N, Smith S, Rose S (2011) The representative concentration pathways: An overview. *Climatic Change*. 109:5–31.
Volz U, Beirne J, Ambrosio N, Fenton A, Mazzacurati E, Renzhi N, Stampe J (2020) Climate change and sovereign risk. London, Tokyo, Singapore, Berkeley: SOAS University of London, Asian Development Bank Institute, World Wide Fund for Nature Singapore, Four Twenty Seven.
Wager S, Hastie T, Efron B (2014) Confidence intervals for random forests: The jackknife and the infinitesimal jackknife. *Journal of Machine Learning Research*. 15:1625–1651.
Zenghelis D, Manley A, Wdowin J (2020) Public debt, public wealth and economic dynamics. Cambridge, UK.
Zenios SA (2021) The risks from climate change to sovereign debt in Europe, Policy Contribution 16/2021, Bruegel.

Appendices

Appendix A- Literature review

Assessing the effect of climate change on sovereign ratings is an inherently interdisciplinary endeavour. We combine several strands of scientific and economic research with practitioner insights from the world of sovereign ratings. This section introduces key themes from climate economics, sovereign risk assessment, and machine learning that underpin our study.

Climate-economy models

Global integrated assessment models (IAMs) such as the DICE model for which Bill Nordhaus was awarded the 2018 Nobel Prize in Economics (for reviews, see Auffhammer 2018; Diaz and Moore 2017) typically operate at the global scale and are used to evaluate economic impacts of various warming scenarios or climate policies, or to calculate the social cost of carbon for use in social cost-benefit analyses (Stern 2008). Although they have been useful in organising economists' thinking about climate-economic relationships, IAMs are notoriously sensitive to assumptions about discount rates, the shape and parameterisation of damage functions, the latency of greenhouse gases in the atmosphere, the degree of climate sensitivity, and the costs and efficacy of investments in mitigation and adaptation (Auffhammer 2018; Diaz and Moore 2017). Whilst some characterize such sensitivities as weaknesses (Pindyck 2013), others find their flexibility useful for integrating advances in economic theory and environmental science into climate policy (Bastien-Olvera and Moore 2020; Dietz and Stern 2015).

The primary limitation of IAMs for the current application – assessing the effect of climate on sovereign creditworthiness – is their high degree of spatial aggregation. Global analyses do not easily translate into country-level risk metrics.[26] For instance, using DICE, Dietz et al. (2016) estimate the representative 'climate value at risk' of global financial assets to be US $2.5 trillion, but do not comment on the distribution of value at risk across countries. While their results demonstrate that restricting warming to 2°C or less make financial sense for risk-neutral and institutional investors, DICE prevents them from making statements about sovereign risk.

[26] Even the regional version of DICE (called RICE), aggregates to eight regions (Nordhaus and Boyer 2000).

A new body of research is emerging that combines climate science with long-run macroeconometric analyses of relationships between temperature and GDP growth at the country-level (Burke et al., 2015; Dell et al., 2012, 2014; Kalkuhl and Wenz 2020; Kahn et al., 2021). Such models are increasingly used to assess country-level impacts[27] of climate change and identify country-specific social costs of carbon (Ricke et al., 2018). In an early contribution, Dell et al. (2012) constructed a 53-year, 125 country panel of weather and macroeconomic data to show that warming significantly reduces growth in poor countries by 1.3 percentage points for each 1C increase in temperature, but that the results are not significant in rich countries. Relaxing Dell et al's (2012) assumption of linearity, Burke et al. (2015) find more extreme and unequal values for the impacts of climate change, with substantial winners and losers from climate change, summing to a net 22.6% of gross world product by 2100. Whilst these models can produce estimates of the economic effects of climate change, their macro structure means they cannot comment on the mechanisms through which these impacts are found (Burke et al., 2015). In contrast, Kahn et al. (2021) develop a stochastic growth model that links deviations of country-specific climate variables (temperature and precipitation) from their historical norms to real output per capita growth. Using data between 1960 and 2014 and 174 countries, they find that persistent deviations of temperature from time-varying and country-specific historical thresholds (i.e., the historical norm) reduces per capita output growth, amounting to around 7% reduction in gross world product by 2100 in the absence of mitigation policies (with the global losses being significantly higher at 13% if the country-specific variability of climate conditions were to rise commensurate to temperature increases). Due to their ability to assess country-level climate impacts (and explicitly modelling changes in the distribution of weather patterns; that is not only averages of climate variables that the climate-macro literature focuses on but also their variability), our baseline model uses Kahn et al. (2021) to inform our assessment of the effects of climate change on sovereign ratings.

To facilitate interpretation and comparability, climate modelling exercises refer to a common set of future scenarios called representative concentration pathways (RCPs). RCPs describe potential trajectories for the annual flow and overall stock of greenhouse gases (GHGs),

[27] Whilst this class of macroeconometric climate studies is able to assess country-level impacts, they are still subject to the limitations of the underlying climate science. For instance, if certain countries are not well represented in global climate models, for instance due to a lack of spatial resolution, then these issues carry over into the economic analyses. We are grateful to an anonymous referee for this insight.

aerosols, and chemically active gases in the atmosphere to 2100 (Moss et al., 2010). Each RCP is named according to its corresponding level of radiative forcing in 2100. For instance, RCP 2.6 refers to a world of stringent climate policy that results in an end-of-century increase in radiative forcing of 2.6 Watts/m2 and corresponds to temperature rise well below 2°C, relative to pre-industrial conditions. In contrast, RCP 8.5 refers to an end-of century increase in radiative forcing (8.5 Watts/m2) and temperature of 5°C, relative to pre-industrial levels.

In terms of policy, the Paris Climate Agreement pledged to limit average warming to 'well below 2°C' and corresponds most closely to RCP 2.6. In contrast, RCP 8.5 is described as the 'worst case' high emissions scenario (Hausfather and Peters 2020; van Vuuren et al., 2011). For comparability with previous literature, we report results for warming scenarios under RCP 2.6 and RCP 8.5.

Climate change and sovereign credit risk

To the best of our knowledge, there is no previous climate science-driven economic analysis of the impact of future climate change related to all types of climate weather events on sovereign ratings. The closest, papers are S&P (2015a,b) and Cevik and Jalles (2020). In S&P (2015b) authors convert the economic outcomes resulting from extreme weather conditions into simplified sovereign rating tool. Findings suggest amongst studied perils earthquakes are the most devastating natural hazard and will likely to put pressure on creditworthiness of sovereigns close to the "edges of Earth's geological plates" such as Chile, Costa Rica, Japan, Panama Peru, Philippines, Taiwan. S&P (2015a) is based on sample of 38 sovereigns and 44 natural catastrophe events arising due to two perils: tropical cyclones and floods. To quantify climate change impact for each sovereign, the authors simulate direct damage to property and infrastructure resulting from given disaster type. The benchmark severity is a natural disaster that would be expected to occur once in every 250 years using a probabilistic model 250 years being a standard benchmark in the reinsurance industry). Simulated impacts take a time horizon up to 2050, and suggest that the impact of climate change via natural disasters is more important for emerging and developing sovereigns than for the advanced economies. Our results vary significantly which might be driven the fact we apply climate-economy models which take account of all natural perils and study much larger sample of sovereigns around the globe. Our trajectories also differ significantly as we are able to predict the climate-adjuested ratings for the years up to 2100.

Offering a backward look rather a future simulation of sovereign ratings Cevik and Jalles (2020) use OLS and ordered response models to regress past sovereign ratings on climate vulnerability, resilience, and the usual macroeconomic indicators for a panel of 67 countries between 1995 and 2017. They find a positive statistically significant effect of climate resilience on ratings, but only mixed results for vulnerability. We advise caution in interpreting these results for several reasons. Many of the countries[28] in their sample were not rated by CRAs until the mid-2000s and may not have many ratings events in the panel. Moreover, the effect of climate change over the period 1995 – 2017 is likely to be small compared to what is expected over the coming century. It could be difficult to identify climate-specific impacts on ratings in the past. More importantly, their approach only considers the effects of climate change on ratings through climate vulnerability and resilience, but ignores the effect of climate change on GDP per capita, GDP growth, or indeed any of the other macroeconomic variables in their model. Finally, we present a number of econometric and methodological challenges in the next section.

Most of the literature on climate and sovereign risk focuses on bond yields rather than ratings (Beirne et al., 2021; Buhr et al., 2018; Capelle-Blancard et al., 2017; Cevik and Jalles 2022a,b; Crifo et al., 2015; Kling et al., 2018). An increasingly common finding is that high climate vulnerability and low resilience increases sovereign borrowing costs, especially for lower income countries (Beirne et al., 2021; Kling et al., 2018).

[28] For instance, Albania's first ever rating was in 2010, Azerbaijan 2008, Bosnia 2008, Fiji 2006, Gabon 2007, Georgia 2005, Mozambique 2004, Nigeria 2006, Seychelles 2006.

Appendix B - Rating scale

Table B.1. Converting S&P's sovereign ratings to a 20-notch numerical scale

Long-term foreign currency issuer rating symbol	Numerical rating	Rating grade	
S&P			
AAA	20	Prime high grade	Investment grade
AA+	19	High grade	
AA	18		
AA-	17		
A+	16	Upper medium grade	
A	15		
A-	14		
BBB+	13	Lower medium grade	
BBB	12		
BBB-	11		
BB+	10	Speculative	Non-investment grade
BB	9		
BB-	8		
B+	7	Highly speculative	
B	6		
B-	5		
CCC+	4	Substantial risks	
CCC	3		
CCC-	2		
CC	1	Extremely speculative	
C	1		
D/SD	1	In default	

Notes: This table presents S&P alphabetical categories translated into 20-notch scale based on S&P's Global Rating Definitions available from:
https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/504352

Appendix C - Robustness to alternative climate-economy models and longer time series

We employ several approaches to testing the robustness of our results. First, we extend the time series of ratings data used to train our ratings prediction model. Our baseline model is trained on 644 sovereign ratings issued by S&P between 2015 and 2020. This time series is chosen because it overlaps with data outputs (climate-adjusted GDP) from our climate-economy model (Kahn et al., 2021) and because ratings issued at any point within this timeframe are still within the standard ratings horizon of 5-10 years.[29] However, most of the countries in our sample have ratings histories that pre-date our 2015 cut-off, meaning a longer time series is available.

To test our model on a longer time series of sovereign ratings, we incorporated data on S&P's sovereign ratings between 2004 and 2020. Tripling the timespan more than doubles our observations number from 644 in the baseline to 1590 in the extended sample. We train the same 6-variable model on the same 109 countries. Table C.1. compares predictive accuracy of our baseline model (columns 2-4) against our extended time series model (columns 5-7). Extending the ratings sample reduces exact matches between observed ratings and our predictions for in-sample, out of sample, and out of sample investment grade ratings. However, this is a random model and variation in predictive accuracy of this magnitude are observed across multiple runs of the model. Interestingly, extending the time series has opposite effects on the accuracy of out of sample tests when we run the model on the full set of 109 countries compared to restricting it to countries with investment grade ratings. Focusing on all 109 countries (columns 2 and 5), we see a decrease in predictive accuracy across the board. In contrast, focusing only on those countries with investment grade ratings (columns 4 and 7), we see slight reduction in exact matches followed by improved accuracy within 1, 2, and 3 notches.

[29] At the time of writing.

Table C.1. Predictive accuracy with an extended time series

Rating range	Our results (2015 – 2020)			Extended sample (2004 – 2020)		
	Whole Sample	**Out of sample (80/20 split)**	**Investment Grade Out of Sample (80/20)**	**Whole Sample**	**Out of sample (80/20 split)**	**Investment Grade Out of Sample (80/20)**
Exact match	68.01%	34.26%	45.45%	57.17	23.12	30.11
1 notch	96.43%	79.63%	87.27%	94.03	61.25	72.73
2 notch	99.84%	94.44%	94.55%	98.36	85.00	94.89
3 notch	-	98.15%	-	99.56	92.81	98.86
Observations	644	536/108	270/55	1590	1270/320	710/176
# of variables	6	6	6	6	6	6
Countries	109	109 / 108	60/55	109	109/109	62/62

Notes: Table presents the predictive capacity of our benchmark random forest model, and an extended time series. Columns 2-4 present the results also found in Table 3. Columns 5-7 present the results when the model is trained on an extended time period.

At first, these results may seem counterintuitive: more data can typically be expected to improve accuracy. However, several unique features of sovereign ratings suggest this may not be the case. First, sovereign ratings have an informal 'lifespan' of 5-10 years, owing to the fact that the political and economic factors on which ratings are based may change substantially over this timeframe. Thus, the inclusion of obsolete data may not improve current predictions. Perhaps more importantly, our extended time series now includes the build-up, duration, and aftermath of the 2008 financial crisis. This was a turbulent period for sovereign ratings and fiscal conditions world-wide. As such, the extended time series may actually introduce more noise than predictive capacity. Finally, results in terms of the simulated impacts of climate change on sovereign ratings were not qualitatively different when the timespan was extended.[30] Thus, for our baseline scenario we focus on ratings issued between 2015 and 2020.

[30] Figures and tables can be provided upon request.

Are our results sensitive to the choice of climate-economic model?

One potential concern with our results is that they could be sensitive to the choice of underlying climate-economic model. Models in the macroeconometric climate literature employ a range of econometric assumptions and specifications, sometimes leading to substantially different conclusions. To assess the sensitivity of our results to the choice of model, we ran the full exercise again using Burke et al. (2015) and Kalkuhl and Wenz (2020) rather than Kahn et al. (2021) for the underlying impacts of climate on GDP and government balances.

Using Burke et al. (2015)

Compared to Kahn et al. (2021), Burke et al. (2015) find more extreme and unequal results across countries. For instance, they find that due to climate change, India will face a 92% reduction in per capita GDP by 2100, whereas Iceland will face a 513% increase.

Both the depths of the modelled losses in hot countries and the peaks of the modelled gains among Northern countries remain outliers in the literature and present challenges for our model. Due to the importance of per capita GDP and its growth rate for simulating ratings, Burke et al.'s extreme results create a larger number of climate-induced upgrades, largely concentrated at the lower end of the ratings scale. Moreover, our interpolative method for extracting the climate-adjusted government balance indicators is less reliable in this setting. S&P (2015b) only assessed the effect of GDP losses of up to 12% on our government performance variables, but Burke et al.'s estimated per capita GDP losses often exceeded this range substantially (e.g., for India, they predict losses of 92%). To avoid extrapolating beyond S&P's data, we capped the negative impacts at 12% GDP loss, and positive impacts at 0% gains.

Figure C.1 Panels A and B illustrate the effect of climate change on investment-grade sovereigns for the year 2100 under Burke et al.'s warming and no warming scenario. Panel A shows that although the results are clearly noisier than under our baseline model using Kahn et al. (2021), we find a similar pattern of substantial downgrades, with greater reductions at the higher end of the scale. T-tests indicate the results are statistically significantly different from zero at the 1% level. Similarly, Panel B depicts our predicted changes in ratings for 2100 using the 'no climate change' scenario from Burke et al.'s model. These results show much closer alignment with current observed ratings. T-tests indicate the changes cannot be statistically significantly distinguished from zero.

Figure C.1. Effect of climate on ratings (2100, RCP 8.5 vs no warming scenario)

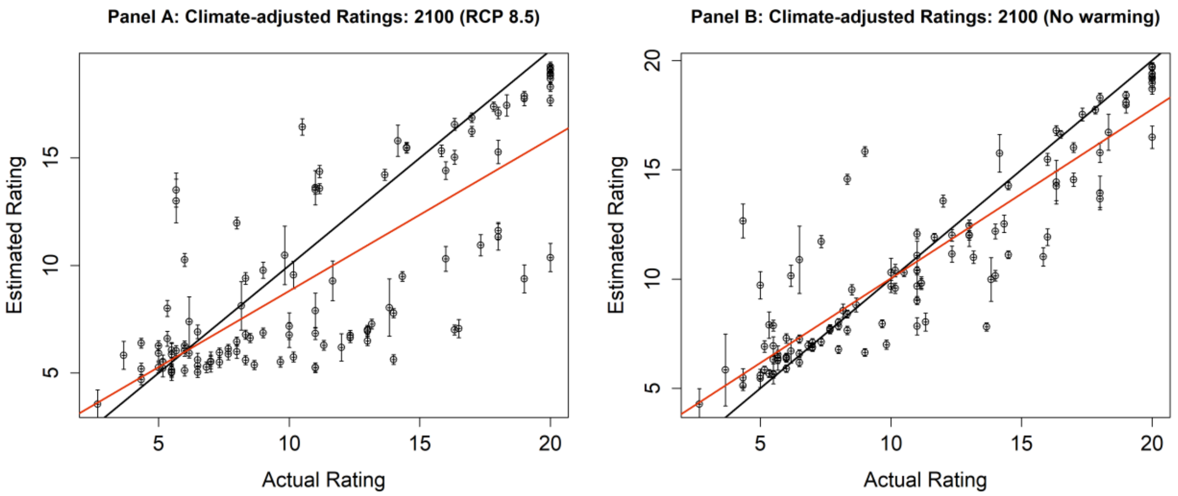

Figure C.1. depicts climate-induced sovereign downgrades by 2100 under RCP 8.5 (Panel A) and a counterfactual scenario in which there is no further warming from 2015 (Panel B), using on Burke et al. (2015) to estimate climate-driven GDP losses. The GDP losses reported in Burke et al. (2015) have considerably greater range than those reported in Kahn et al. (2021) or Kalkuhl and Wenz (2020). However, the results are qualitatively similar: limiting warming will reduce downward pressure on ratings, and downgrades will be most severe at the higher end of the rating scale.

Using Kalkuhl and Wenz (2020)

Using the data provided by Kalkuhl and Wenz (2020), we estimate the impact of a decline in GDP on sovereign credit ratings for the periods 2030, 2050, 2070 and 2100. Ultimately, we once again find qualitatively similar results using Kalkuhl and Wenz (2020) to those reported in the paper, based on Kahn et al. (2021).

Kalkuhl and Wenz (2020) estimate the gross regional product under RCP 8.5 for more than 1500 regions in 77 countries. In order to aggregate this for our country level analysis we perform the following procedure. First, we take their backward-looking panel data and assign year groupings. That is, we identify country groups for the years 2001-2003, 2005-2007 and 2012-2014. On this basis we then calculate regional GDP weightings for these year groupings. We sum the regional GDP and calculate the proportionality of each region’s GDP against the total. We then take the regional weightings forward to estimate country-level GDP loss. As some of the data is incomplete, we select the most recent year grouping for each country.

Second, we take the product of the regional weighting and the GDP estimate for each of the forward-looking years in their data. Finally, we take the sum of the weighted GDP damage estimates for each country's region to arrive at a country-level estimate for GDP losses.

We apply these new GDP losses to our model following the same procedure as for Kahn et al. (2021). Figure C.2 below depicts our primary finding. The graph below shows a unitary solid black line which would indicate an estimated rating to be the same as the actual rating. Further, we also plot the linear estimations for the actual rating regressed on the estimated rating for the years 2030, 2050, 2070 and 2100 from top to bottom. The data points plotted represent the observations for 2100. Our results show a similar outcome for Kalkuhl and Wenz (2020) as they do for the Kahn et al. (2021) data.

Figure C.2. Estimated ratings using Kalkuhl and Wenz (2020)

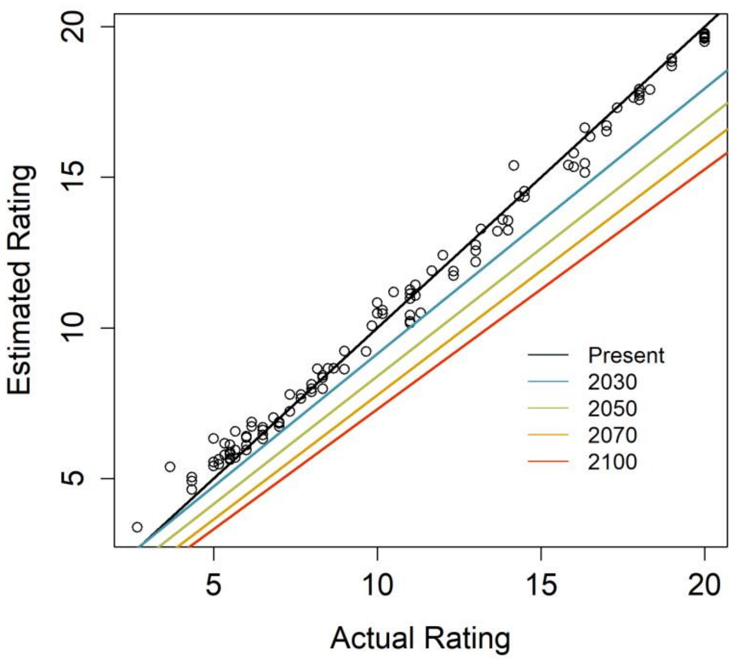

Figure C.2. depicts climate-induced sovereign downgrades by 2030, 2050, 2070, and 2100 under RCP 8.5 using Kalkuhl and Wenz (2020) to estimate climate-driven GDP losses. Once again we find qualitatively similar results: limiting warming will reduce downward pressure on ratings and this downward pressure increases over time. Compared to results based on Kahn et al. (2021), there are slightly larger downgrades in the upper-mid range (10-15) of the rating scale, though severe downgrades amongst the highest-rated sovereigns are still observed.

Appendix D - Additional cost of sovereign and corporate borrowing due to climate-induced sovereign downgrades

Table D.1. Additional cost of sovereign borrowing due to climate-induced sovereign downgrades (RCP 2.6, 2100)

Sovereign	Outstanding sovereign debt ($ bn)	Sovereign downgrade (notches)	Cost of sovereign borrowing ($ bn) (lower bound)	Cost of sovereign borrowing ($ bn) (higher bound)
Albania	6.50	0.09	0.00	0.00
Australia	384.50	0.78	0.24	0.36
Austria	231.70	0.34	0.06	0.09
Bangladesh	45.50	0.58	0.02	0.03
Belgium	436.90	0.46	0.16	0.24
Benin	3.90	0.18	0.00	0.00
Botswana	1.10	0.93	0.00	0.00
Bulgaria	10.80	0.11	0.00	0.00
Canada	557.10	1.84	0.82	1.23
Cape Verde	1.30	0.07	0.00	0.00
Chile	70.50	7.11	0.40	0.60
China	2464.40	1.80	3.55	5.32
Colombia	129.80	1.27	0.13	0.20
Costa Rica	31.40	0.78	0.02	0.03
Czech Republic	70.20	0.72	0.04	0.06
Denmark	91.70	0.37	0.03	0.04
Dominican Republic	28.70	0.26	0.01	0.01
Estonia	0.10	0.39	0.00	0.00
Finland	118.10	0.23	0.02	0.03
France	2026.10	0.23	0.37	0.56
Georgia	2.60	0.47	0.00	0.00
Germany	1254.30	0.48	0.48	0.72
India	1365.30	3.73	4.07	6.11
Indonesia	290.60	3.38	0.79	1.18
Israel	237.90	0.20	0.04	0.06
Japan	10396.20	1.42	11.81	17.72
Jordan	29.50	0.35	0.01	0.01
Kazakhstan	26.80	1.25	0.03	0.04
Kenya	37.00	0.46	0.01	0.02
South Korea	589.50	1.80	0.85	1.27
Kuwait	16.50	0.51	0.01	0.01
Latvia	11.20	0.18	0.00	0.00
Lebanon	88.60	0.13	0.01	0.01
Luxembourg	11.70	0.28	0.00	0.00

Malaysia	189.80	0.85	0.13	0.19

Table D.1. Continued

Sovereign	Outstanding sovereign debt ($ bn)	Sovereign downgrade (notches)	Cost of sovereign borrowing ($ bn) (lower bound)	Cost of sovereign borrowing ($ bn) (higher bound)
Mexico	386.40	0.29	0.09	0.13
Morocco	67.20	1.09	0.06	0.09
Netherlands	341.40	0.51	0.14	0.21
New Zealand	52.70	2.29	0.10	0.14
Macedonia	4.00	0.84	0.00	0.00
Norway	49.80	0.44	0.02	0.03
Panama	23.60	0.64	0.01	0.02
Peru	49.10	1.24	0.05	0.07
Philippines	134.50	3.60	0.39	0.58
Poland	222.40	0.63	0.11	0.17
Portugal	224.9	0.28	0.05	0.08
Qatar	100.20	0.08	0.01	0.01
Rwanda	1.40	0.04	0.00	0.00
Senegal	6.00	0.20	0.00	0.00
Serbia	14.30	0.81	0.01	0.01
Slovakia	42.90	1.57	0.05	0.08
Slovenia	31.00	1.37	0.03	0.05
South Africa	213.30	0.79	0.13	0.20
Spain	1096.2	0.37	0.32	0.49
Sri Lanka	57.20	0.24	0.01	0.02
Suriname	1.7	0.13	0.00	0.00
Sweden	119.70	0.61	0.06	0.09
Switzerland	68.60	2.29	0.13	0.19
Thailand	180.20	0.67	0.10	0.14
United Kingdom	2710.70	0.77	1.67	2.50
United States	16673.40	1.25	16.67	25.01
Vietnam	53.70	0.04	0.00	0.00
Full sample total	**44184.30**	**0.92**	**44.33**	**66.49**

Notes: Translating climate-induced sovereign downgrades into increased sovereign cost of borrowing by 2100 under RCP 2.6 scenario. Dataset includes 55 downgraded sovereigns and their outstanding sovereign debt figures for 2019 obtained from S&P SRIs. Conversion between sovereign downgrades into yields for lower bound is based on Afonso et al. (2012) and for higher bound on Gande and Parsley (2005), whereby 1 notch sovereign downgrade increases sovereign bond spread by 0.08% and 0.12% respectively.

Table D.2. Additional cost of sovereign borrowing due to climate-induced sovereign downgrades (RCP 8.5, 2100)

Sovereign	Outstanding sovereign debt ($ bn)	Sovereign downgrade (notches)	Cost of sovereign borrowing ($ bn) (lower bound)	Cost of sovereign borrowing ($ bn) (higher bound)
Albania	6.50	1.57	0.01	0.01
Australia	384.50	3.53	1.09	1.63
Austria	231.70	2.17	0.40	0.60
Bangladesh	45.50	1.41	0.05	0.08
Belgium	436.90	1.11	0.39	0.58
Benin	3.90	1.03	0.00	0.00
Bolivia	4.90	0.60	0.00	0.00
Botswana	1.10	3.47	0.00	0.00
Brazil	1032.60	1.58	1.31	1.96
Bulgaria	10.80	3.16	0.03	0.04
Canada	557.10	4.72	2.10	3.16
Cape Verde	1.30	0.46	0.00	0.00
Chile	70.50	7.43	0.42	0.63
China	2464.40	6.53	12.87	19.31
Colombia	129.80	4.40	0.46	0.69
Costa Rica	31.40	0.84	0.02	0.03
Croatia	34.60	0.96	0.03	0.04
Cyprus	13.80	0.07	0.00	0.00
Czech Republic	70.20	2.65	0.15	0.22
Denmark	91.70	0.82	0.06	0.09
Dominican Republic	28.70	0.93	0.02	0.03
Egypt	253.60	0.15	0.03	0.05
Estonia	0.10	1.40	0.00	0.00
Fiji	2.30	0.55	0.00	0.00
Finland	118.10	0.14	0.01	0.02
France	2026.10	2.70	4.38	6.56
Georgia	2.60	1.68	0.00	0.01
Germany	1254.30	0.78	0.78	1.17
Guatemala	15.90	1.58	0.02	0.03
Honduras	6.80	0.36	0.00	0.00
Hungary	93.10	2.14	0.16	0.24
India	1365.30	5.55	6.06	9.09
Indonesia	290.60	4.06	0.94	1.42
Israel	237.90	0.86	0.16	0.25
Italy	2225.30	0.53	0.94	1.42
Japan	10396.20	2.56	21.29	31.94
Jordan	29.50	1.68	0.04	0.06

Table D.2. Continued				
Sovereign	**Outstanding sovereign debt ($ bn)**	**Sovereign downgrade (notches)**	**Cost of sovereign borrowing ($ bn) (lower bound)**	**Cost of sovereign borrowing ($ bn) (higher bound)**
Kazakhstan	26.80	4.65	0.10	0.15
Kenya	37.00	0.89	0.03	0.04
South Korea	589.50	2.57	1.21	1.82
Kuwait	16.50	0.60	0.01	0.01
Latvia	11.20	2.33	0.02	0.03
Lithuania	16.90	1.79	0.02	0.04
Luxembourg	11.70	0.76	0.01	0.01
Malaysia	189.80	6.07	0.92	1.38
Mexico	386.40	5.55	1.72	2.57
Mongolia	4.90	0.40	0.00	0.00
Morocco	67.20	5.02	0.27	0.40
Netherlands	341.40	0.81	0.22	0.33
New Zealand	52.70	2.69	0.11	0.17
Macedonia	4.00	1.57	0.01	0.01
Norway	49.80	0.57	0.02	0.03
Pakistan	141.90	0.24	0.03	0.04
Panama	23.60	3.59	0.07	0.10
Paraguay	5.20	0.95	0.00	0.01
Peru	49.10	5.25	0.21	0.31
Philippines	134.50	3.76	0.40	0.61
Poland	222.40	4.13	0.73	1.10
Portugal	224.90	1.23	0.22	0.33
Qatar	100.20	0.66	0.05	0.08
Romania	88.90	3.04	0.22	0.32
Russia	191.40	0.42	0.06	0.10
Rwanda	1.40	0.67	0.00	0.00
Saudi Arabia	167.50	0.31	0.04	0.06
Senegal	6.00	0.94	0.00	0.01
Serbia	14.30	1.98	0.02	0.03
Slovakia	42.90	5.90	0.20	0.30
Slovenia	31.00	2.87	0.07	0.11
South Africa	213.30	3.15	0.54	0.81
Spain	1096.20	2.85	2.50	3.75
Sri Lanka	57.20	1.12	0.05	0.08
Suriname	1.70	0.61	0.00	0.00
Sweden	119.70	1.30	0.12	0.19
Switzerland	68.60	2.62	0.14	0.22
Thailand	180.20	2.28	0.33	0.49
Turkey	204.50	1.30	0.21	0.32
Ukraine	51.20	0.02	0.00	0.00
United Kingdom	2710.70	3.46	7.50	11.25

Table D.2. Continued

Sovereign	Outstanding sovereign debt ($ bn)	Sovereign downgrade (notches)	Cost of sovereign borrowing ($ bn) (lower bound)	Cost of sovereign borrowing ($ bn) (higher bound)
United States	16673.40	4.68	62.43	93.64
Uruguay	27.10	2.70	0.06	0.09
Vietnam	53.70	2.25	0.10	0.14
Full sample total	**48678.10**	**2.18**	**135.24**	**202.86**

Notes: Translating climate-induced sovereign downgrades into increased sovereign cost of borrowing by 2100 under RCP 8.5 scenario. Dataset includes 80 downgraded sovereigns and their outstanding sovereign debt figures for 2019 obtained from S&P SRIs. Conversion between sovereign downgrades into yields for lower bound is based on Afonso et al. (2012) and for higher bound on Gande and Parsley (2005), whereby 1 notch sovereign downgrade increases sovereign bond spread by 0.08% and 0.12% respectively.

Table D.3. Additional cost of corporate debt due to climate-induced sovereign downgrades (RCP 2.6, 2100)

Sovereign	Sovereign downgrade (notches)	Outstanding corporate debt ($ bn)	Increase in cost of debt ($ bn) lower bound	Increase in cost of debt ($ bn) higher bound
Australia	0.78	213	0.08	0.14
Austria	0.34	44	0.01	0.01
Belgium	0.46	70	0.02	0.03
Bulgaria	0.11	2	0.00	0.00
Canada	1.84	515	0.45	0.80
Chile	7.11	89	0.30	0.53
China	1.80	4061	3.51	6.14
Czech Republic	0.72	15	0.01	0.01.
Denmark	0.37	25	0.00	0.01
Estonia	0.39	1	0.00	0.00
Finland	0.23	39	0.00	0.01
France	0.23	777	0.09	0.15
Germany	0.48	241	0.06	0.10
Israel	0.20	66	0.01	0.01
Japan	1.42	845	0.58	1.01
Luxembourg	0.28	30	0.00	0.01
Malaysia	0.85	176	0.07	0.13
Netherlands	0.51	180	0.04	0.08
Norway	0.44	91	0.02	0.03
Peru	1.24	21	0.01	0.02
Philippines	3.60	14	0.02	0.04
Poland	0.63	20	0.01	0.01
Portugal	0.28	37	0.00	0.01
Slovakia	1.57	5	0.00	0.01
Slovenia	1.37	1	0.00	0.00
Spain	0.37	138	0.02	0.04
Sweden	0.61	9	0.00	0.00
Thailand	0.67	116	0.04	0.07
United Kingdom	0.77	564	0.21	0.36
United States	1.25	7126	4.28	7.48
Total BIS	**1.03**	**15531**	**9.85**	**17.23**

Notes: Translating climate-induced sovereign downgrades into increased corporate cost of debt by 2100 under RCP 2.6 scenario. Data availability from BIS on corporate debt restricts our sample to 28 countries. To calculate the value of corporate debt affected by sovereign downgrades we first convert the sovereign rating changes into sovereign yield which we then convert into corporate sovereign yield. To convert sovereign ratings into yields we use lower bond (0.08%) from Afonso et al. (2012) and higher bound (0.12%) from Gande and Parsley (2005). To then translate these into corporate spreads we use Almeida et al. (2017)' conversions, with 0.6 for lower bound and 0.7 for higher bound. We multiply sovereign rating changes (see column 2) by an amount of outstanding debt at end-June 2020 (column 3) and 0.00048 for a lower bound (0.08%*0.6) and 0.00084 (0.12%*0.7) for a higher bound.

Table D.4. Additional cost of corporate debt due to climate-induced sovereign downgrades (RCP 8.5, 2100)

Sovereign	**Sovereign downgrade (notches)**	**Outstanding corporate debt ($ bn)**	**Increase in cost of debt ($ bn) lower bound**	**Increase in cost of debt ($ bn) higher bound**
Australia	3.53	213	0.36	0.63
Austria	2.17	44	0.05	0.08
Belgium	1.11	70	0.04	0.07
Bulgaria	3.16	2	0.00	0.01
Canada	4.72	515	1.17	2.04
Chile	7.43	89	0.32	0.56
China	6.53	4061	12.73	22.28
Croatia	0.96	3	0.00	0.00
Czech Republic	2.65	15	0.02	0.03
Denmark	0.82	25	0.01	0.02
Estonia	1.40	1	0.00	0.00
Finland	0.14	39	0.00	0.00
France	2.70	777	1.01	1.76
Germany	0.78	241	0.09	0.16
Hungary	2.14	3	0.00	0.01
Israel	0.86	66	0.03	0.05
Italy	0.53	152	0.04	0.07
Japan	2.56	845	1.04	1.82
Lithuania	1.79	1	0.00	0.00
Luxembourg	0.76	30	0.01	0.02
Malaysia	6.07	176	0.51	0.90
Netherlands	0.81	180	0.07	0.12
Norway	0.57	91	0.02	0.04
Peru	5.25	21	0.05	0.09
Philippines	3.76	14	0.03	0.04
Poland	4.13	20	0.04	0.07
Portugal	1.23	37	0.02	0.04
Slovakia	5.90	5	0.01	0.02
Slovenia	2.87	1	0.00	0.00
Spain	2.85	138	0.19	0.33
Sweden	1.30	9	0.01	0.01
Thailand	2.28	116	0.13	0.22
Turkey	1.30	9	0.01	0.01
United Kingdom	3.46	564	0.94	1.64
United States	4.68	7126	16.01	28.01
Total BIS	**2.66**	**15699**	**34.94**	**61.15**

Notes: Translating climate-induced sovereign downgrades into increased corporate cost of debt by 2100 under RCP 8.5 scenario. Data availability from BIS on corporate debt restricts our sample to 34 countries. To calculate the value of corporate debt affected by sovereign downgrades we first convert the sovereign rating changes into sovereign yield which we then convert into corporate sovereign yield. To convert sovereign ratings into yields we use lower bond (0.08%) from Afonso et al. (2012) and higher bound (0.12%) from Gande and Parsley (2005). To then translate these into corporate spreads we use Almeida et al. (2017)' conversions, with 0.6 for lower bound and 0.7 for higher bound. We multiply sovereign rating changes (see column 2) by an amount of outstanding debt at end-June 2020 (column 3) and 0.00048 for a lower bound (0.08%*0.6) and 0.00084 (0.12%*0.7) for a higher bound.

Appendix E - The effect of increased temperature volatility on sovereign ratings

Table E.1. Climate-adjusted Sovereign Credit Ratings by Scenario, with increased temperature volatility (2030)

	RCP 2.6		RCP 8.5	
Sovereign	**Baseline**	**Increased Volatility**	**Baseline**	**Increased Volatility**
Albania	6.99	6.95	6.88	6.76
Angola	6.21	6.20	6.25	6.27
Argentina	5.57	5.74	5.66	5.96
Australia	19.31	19.26	19.23	18.58
Austria	18.70	18.69	18.65	18.25
Azerbaijan	10.44	10.45	10.43	10.44
Bahamas	10.55	10.59	10.54	10.56
Bangladesh	7.92	6.50	7.88	3.75
Belarus	6.70	6.71	6.85	7.00
Belgium	17.50	17.57	17.44	17.41
Belize	5.16	5.15	5.22	5.30
Benin	6.80	6.80	6.81	6.79
Bolivia	8.67	8.68	8.69	8.68
Bosnia and Herzegovina	6.57	6.59	6.74	6.87
Botswana	13.00	13.02	12.85	12.26
Brazil	8.64	8.64	8.60	8.62
Bulgaria	11.29	11.38	11.35	11.09
Burkina Faso	6.00	6.01	6.08	6.13
Cameroon	6.39	6.39	6.44	6.50
Canada	19.07	18.87	18.60	17.16
Cape Verde	5.97	5.99	5.94	5.90
Chile	14.41	13.57	14.11	11.98
China	14.99	15.14	14.48	14.26
Colombia	10.07	10.08	10.00	8.58
Congo	5.45	5.44	5.47	5.50
Congo D.R.	5.12	5.11	5.35	5.48
Costa Rica	7.78	7.74	7.73	7.58
Croatia	9.96	10.08	9.95	10.02
Cyprus	10.83	10.85	10.79	10.67
Czech Republic	16.21	16.28	16.14	15.86
Denmark	19.63	19.67	19.61	19.44
Dominican Republic	7.69	7.74	7.65	7.57
Ecuador	6.30	6.38	6.36	6.68
Egypt	5.69	5.69	5.67	5.67
El Salvador	5.79	5.78	5.84	5.83

Table E.1. Cont.

Sovereign	RCP 2.6 Baseline	RCP 2.6 Increased Volatility	RCP 8.5 Baseline	RCP 8.5 Increased Volatility
Estonia	16.56	16.64	16.47	16.18
Fiji	7.91	7.99	8.03	8.39
Finland	18.80	18.93	18.78	18.77
France	17.67	17.71	17.59	17.36
Georgia	7.88	7.91	7.84	7.44
Germany	19.53	19.70	19.47	19.37
Ghana	5.80	5.82	5.82	5.84
Greece	7.00	7.41	7.06	7.78
Guatemala	8.45	8.45	8.51	8.53
Honduras	7.72	7.72	7.73	7.72
Hungary	11.51	11.56	11.53	11.39
Iceland	15.43	15.43	15.44	15.50
India	9.78	9.41	9.16	7.83
Indonesia	9.37	9.11	8.91	7.69
Iraq	6.43	6.40	6.50	6.68
Ireland	16.65	16.65	16.65	16.63
Israel	16.27	16.31	16.23	16.08
Italy	11.90	11.90	11.80	11.76
Japan	15.75	15.63	15.65	14.98
Jordan	7.11	7.03	7.01	6.19
Kazakhstan	11.01	10.86	10.91	10.17
Kenya	6.64	6.67	6.60	6.53
Korea	17.50	16.84	17.42	15.80
Kuwait	17.51	17.51	17.49	17.47
Latvia	14.23	14.30	14.13	13.62
Lebanon	4.65	4.60	4.61	4.39
Lithuania	14.47	14.54	14.43	14.31
Luxembourg	19.72	19.70	19.68	19.56
Malaysia	13.01	13.10	12.67	12.52
Mexico	12.67	12.70	12.55	12.10
Mongolia	5.68	5.69	5.67	5.69
Morocco	9.87	9.91	9.60	8.92
Mozambique	3.41	3.49	3.44	3.54
Netherlands	19.53	19.58	19.48	19.40
New Zealand	17.79	14.61	17.73	9.89
Nicaragua	5.89	5.89	5.95	5.98
Nigeria	6.82	6.82	6.87	6.92
North Macedonia	8.21	8.24	8.24	7.10
Norway	19.59	19.64	19.57	19.55
Oman	10.48	10.48	10.49	10.42
Pakistan	5.65	5.63	5.62	5.51

Table E.1. Cont.

Sovereign	RCP 2.6 Baseline	RCP 2.6 Increased Volatility	RCP 8.5 Baseline	RCP 8.5 Increased Volatility
Panama	11.71	11.70	11.62	11.47
Papua New Guinea	6.69	6.69	6.73	6.73
Paraguay	9.21	8.81	9.17	7.94
Peru	11.88	11.74	11.78	8.80
Philippines	11.19	10.66	10.70	9.01
Poland	12.75	12.96	12.54	12.11
Portugal	10.76	10.75	10.74	10.20
Qatar	17.20	17.23	17.14	17.12
Romania	11.13	11.13	11.11	9.43
Russia	11.23	11.27	11.20	11.17
Rwanda	6.44	6.44	6.45	6.46
Saudi Arabia	14.36	14.41	14.37	14.39
Senegal	6.71	6.74	6.70	6.66
Serbia	8.35	8.29	8.25	7.65
Slovakia	14.75	14.61	14.34	12.53
Slovenia	15.14	15.01	14.88	14.50
South Africa	8.95	8.89	8.77	7.67
Spain	13.40	13.42	13.25	13.13
Sri Lanka	6.24	6.24	6.19	6.13
Suriname	6.52	6.40	6.46	5.91
Sweden	19.44	19.50	19.40	19.16
Switzerland	19.63	19.37	19.40	18.20
Tajikistan	5.79	5.79	5.88	5.94
Thailand	12.34	12.34	12.32	11.27
Trinidad and Tobago	13.35	13.39	13.34	13.44
Turkey	8.70	8.55	8.56	7.68
Uganda	6.12	6.12	6.15	6.17
Ukraine	5.89	5.90	5.91	5.79
United Kingdom	17.54	17.56	17.42	16.76
United States	18.51	18.43	18.24	17.54
Uruguay	12.36	12.36	12.33	12.16
Vietnam	8.31	8.29	8.26	6.78
Zambia	5.59	5.62	5.63	5.66

Notes: Table E.1. compares ratings in 2030, with and without increased temperature volatility. Columns 2-3 report results under RCP 2.6. Columns 4-5 report results under RCP 8.5.

Table E.2. Climate-adjusted Sovereign Credit Ratings by Scenario, with increased temperature volatility (2050)

	RCP 2.6		RCP 8.5	
Sovereign	**Baseline**	**Increased Volatility**	**Baseline**	**Increased Volatility**
Albania	6.95	6.88	6.20	5.13
Angola	6.20	6.18	6.24	6.25
Argentina	5.69	6.00	5.95	6.11
Australia	19.29	19.13	18.50	16.51
Austria	18.70	18.62	18.19	16.80
Azerbaijan	10.44	10.49	10.43	10.53
Bahamas	10.57	10.60	10.55	10.98
Bangladesh	7.89	3.76	7.22	2.98
Belarus	6.70	6.74	7.06	8.35
Belgium	17.52	17.76	17.41	17.02
Belize	5.15	5.14	5.36	5.24
Benin	6.82	6.87	6.68	6.61
Bolivia	8.68	8.69	8.31	8.28
Bosnia and Herzegovina	6.70	6.76	7.13	7.23
Botswana	13.01	13.16	12.00	10.79
Brazil	8.64	8.66	8.22	7.92
Bulgaria	11.39	10.69	11.05	8.37
Burkina Faso	6.00	5.98	6.13	6.27
Cameroon	6.39	6.40	6.50	6.48
Canada	18.89	18.22	16.20	15.34
Cape Verde	5.99	5.93	5.86	5.68
Chile	13.30	9.86	10.35	9.42
China	15.22	15.35	13.41	12.70
Colombia	10.08	10.10	9.19	6.94
Congo	5.44	5.43	5.55	5.60
Congo D.R.	5.10	5.05	5.92	6.25
Costa Rica	7.67	7.32	7.07	6.91
Croatia	10.04	10.16	9.85	9.57
Cyprus	10.84	10.87	10.66	10.03
Czech Republic	16.23	16.42	15.92	14.51
Denmark	19.64	19.72	19.53	18.88
Dominican Republic	7.72	7.83	7.54	7.30
Ecuador	6.33	6.66	6.57	3.83
Egypt	5.68	5.68	5.68	5.62
El Salvador	5.78	5.80	5.92	5.85
Estonia	16.63	16.70	16.20	15.63
Fiji	8.04	8.29	8.42	7.22

Table E.2 Cont.

Sovereign	RCP 2.6 Baseline	RCP 2.6 Increased Volatility	RCP 8.5 Baseline	RCP 8.5 Increased Volatility
Finland	18.88	19.02	18.78	18.76
France	17.71	17.75	17.19	16.13
Georgia	7.88	7.92	7.67	6.47
Germany	19.57	19.73	19.41	19.15
Ghana	5.80	5.83	5.85	5.88
Greece	7.13	7.82	7.81	7.35
Guatemala	8.43	8.45	8.51	8.39
Honduras	7.71	7.68	7.63	7.70
Hungary	11.53	11.61	11.50	8.84
Iceland	15.43	15.43	15.49	15.73
India	9.34	8.02	6.36	5.58
Indonesia	9.03	7.83	7.24	6.99
Iraq	6.43	6.44	6.66	6.98
Ireland	16.66	16.65	16.60	16.59
Israel	16.28	16.39	16.12	15.63
Italy	11.90	11.90	11.81	11.93
Japan	15.62	14.72	14.64	13.92
Jordan	7.08	6.76	6.54	5.71
Kazakhstan	10.84	9.90	10.18	9.07
Kenya	6.65	6.69	6.49	6.39
Korea	17.35	15.69	16.39	7.72
Kuwait	17.51	17.58	17.48	17.42
Latvia	14.25	14.40	13.65	12.52
Lebanon	4.54	4.29	4.29	4.15
Lithuania	14.51	14.63	14.35	12.81
Luxembourg	19.73	19.71	19.62	19.27
Malaysia	13.15	13.27	11.96	11.03
Mexico	12.70	12.72	10.72	8.36
Mongolia	5.68	5.71	5.68	5.40
Morocco	9.90	10.07	8.03	6.56
Mozambique	3.41	3.53	3.59	3.94
Netherlands	19.53	19.60	19.44	19.14
New Zealand	17.55	7.61	16.81	7.01
Nicaragua	5.87	5.89	5.98	6.11
Nigeria	6.81	6.80	6.84	6.88
North Macedonia	8.22	6.95	7.16	6.40
Norway	19.60	19.66	19.56	19.37
Oman	10.48	10.50	10.46	10.03
Pakistan	5.64	5.66	5.46	5.26
Panama	11.70	11.70	11.13	10.35

Table E.2 Cont.				
	RCP 2.6		**RCP 8.5**	
Sovereign	**Baseline**	**Increased Volatility**	**Baseline**	**Increased Volatility**
Papua New Guinea	6.69	6.75	6.64	6.66
Paraguay	9.19	7.87	8.83	3.77
Peru	11.84	11.16	10.08	7.82
Philippines	10.51	8.91	8.78	8.90
Poland	12.88	13.24	12.22	9.71
Portugal	10.75	10.49	10.25	9.74
Qatar	17.24	17.28	17.06	16.90
Romania	11.13	10.89	9.36	7.84
Russia	11.27	11.27	10.78	10.16
Rwanda	6.44	6.46	6.33	5.95
Saudi Arabia	14.38	14.46	14.36	14.17
Senegal	6.79	6.81	6.63	6.54
Serbia	8.33	7.94	7.60	7.04
Slovakia	14.68	14.15	12.28	10.11
Slovenia	14.95	14.76	13.79	13.16
South Africa	8.94	8.71	7.84	6.57
Spain	13.42	13.45	12.72	11.98
Sri Lanka	6.25	6.25	5.98	5.77
Suriname	6.49	5.98	6.32	4.88
Sweden	19.43	19.52	19.31	18.30
Switzerland	19.30	18.01	17.87	17.41
Tajikistan	5.79	5.80	6.13	6.25
Thailand	12.33	12.56	12.04	10.53
Trinidad and Tobago	13.39	13.46	13.37	13.60
Turkey	8.66	8.34	8.26	6.91
Uganda	6.12	6.12	6.17	6.17
Ukraine	5.89	5.95	5.77	5.29
United Kingdom	17.55	17.61	16.93	14.85
United States	18.39	18.03	16.45	14.28
Uruguay	12.36	12.31	11.73	10.09
Vietnam	8.31	8.28	7.85	6.07
Zambia	5.61	5.65	5.50	5.26

Notes: Table E.2. compares ratings in 2050, with and without increased temperature volatility. Columns 2-3 report results under RCP 2.6. Columns 4-5 report results under RCP 8.5.