Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness

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Outline

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2. Empirical framework
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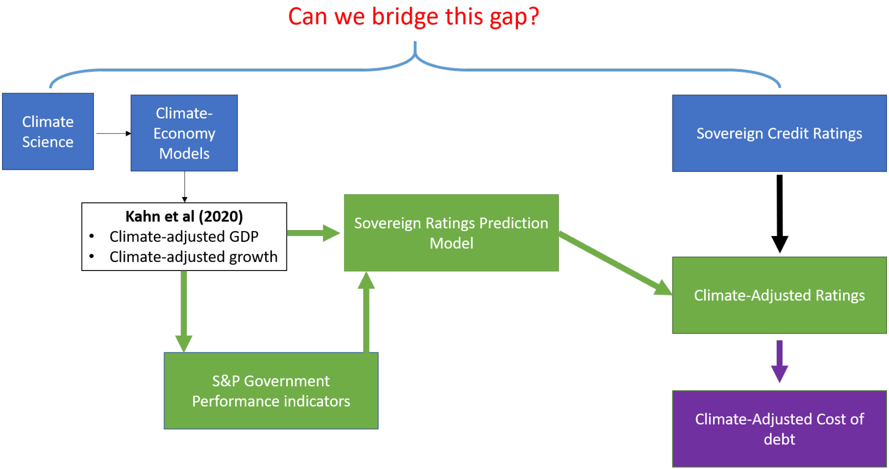
1. Bridging the gap



1. Climate time travel

- Keeping everything the same..
- Except climate and its impact on key macroeconomic indicators
- How different will our sovereign ratings be? How much will this cost? And, what are the policy implications of this?

2. Machine Learning Approach

- Two step modelling problem;
    1. Produce a reliable, accurate model
    2. Estimate it with climate-adjusted data
- Sovereign rating prediction;
    - Linear regressions
    - Logit/probit models
    - Limitations
- Solution;
    - Non-linear modelling;
    - Machine learning algorithms
    - Our improvements;
        - Ability to integrate climate economics
        - Parsimony

2. Random Forests

- Random forest seemed to be the most obvious modelling approach;
  - Some literature had implemented this before with success (over and above other ML algorithms)
  - Handled non-linearities
  - Adaptations to the algorithm enabled us to remain as close as possible to the actual practice of sovereign rating assessment;
    - Rating ranges (confidence intervals)

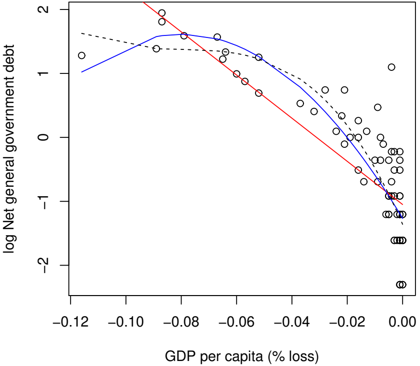
2. Climate-adjusted ratings prediction

- Climate economics gives us GDP for various climate scenarios
- Typical classification algorithms for sovereign ratings may include up to 15-20 factors
- Problem: We needed more data to enable a robust and accurate assessment

2. Climate-adjusted ratings prediction

- Key government performance indicators provide excellent information for ratings prediction
- We needed climate-adjusted versions
- S&P assess impact of natural disasters on government balances
- This enabled us to add these variables to our model
- We used S&P's assessment on what would happen to various government balance variables as a result of GDP losses. We derived a simple 3^{rd} order polynominal and applied this to our GDP data.

2. Climate-adjusted government performance indicators



- This model uses uses the government variable as the outcome, and GDP losses as the input. We add polynomial terms on the right-hand side.

- With the following variables;
  - **GDP per capita**
  - **GDP growth rate**
  - Net General Govt Debt/GDP
  - Narrow Net External Debt/CARs
  - Current Account Balance/GDP
  - General Government Balance/GDP

2. Data

- Sample
  - 108 countries
  - 2004 - 2019
  - Model is calibrated on data from 2015 to improve reliability
- Variables
  - GDP per capita
  - GDP growth rate
  - Net General Govt Debt/GDP
  - Narrow Net External Debt/CARs
  - Current Account Balance/GDP
  - General Government Balance/GDP

2. Calibrating the RF algorithm

- Once we established that we were able to produce climate-adjusted versions of key variables, we set to work on building our RF model
- The underlying objective is to split data
- We split data by selecting the values of given variables that lead to the best split
- This is the split which results in the least mean squared error
- We keep this process going until we are no longer able to split the data with the information available or until we have a category with 5 observations.

2. Calibrating the RF algorithm

- Procedure;
  - We produce a regression forest, with 2,000 individual decision trees.
  - Each tree operates like an ordinary decision tree algorithm.
  - Each tree splits the data on a randomly selected subset of variables (2 are randomly selected for each split).
  - ...and a random sample of the training dataset is assigned to each tree
  - with replacement (bagging)

2. The Simulation - Pinball machine

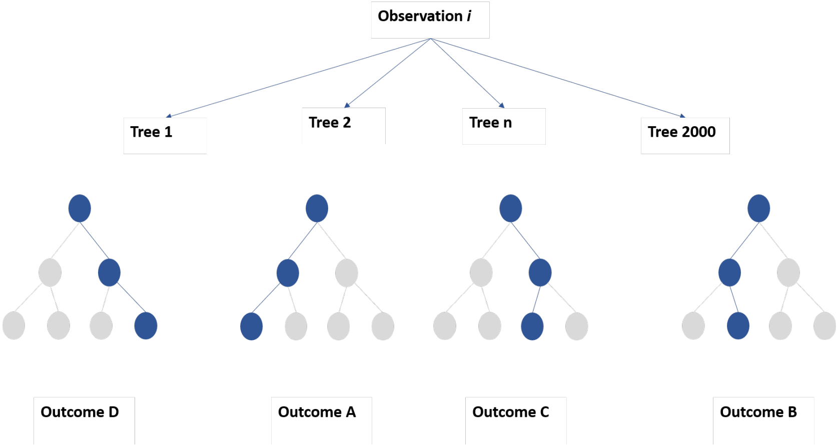
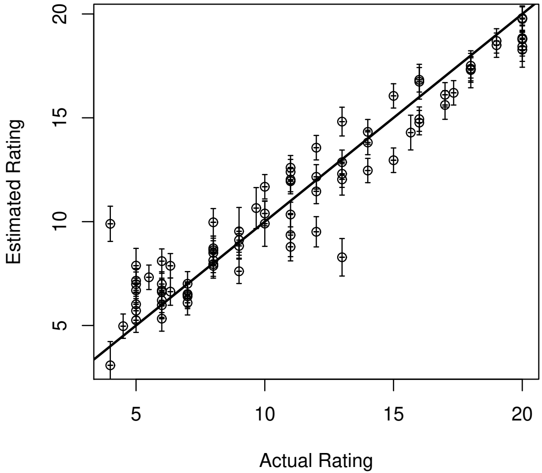


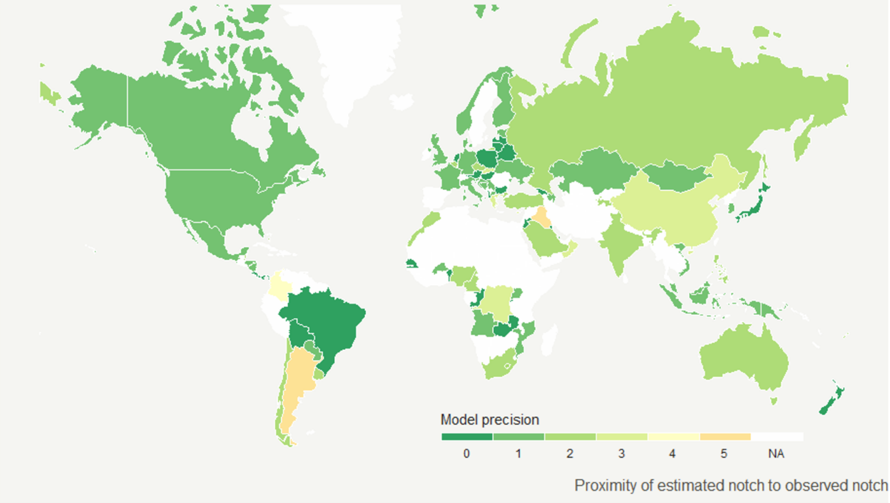
Figure: Random forest classification

2. Model accuracy 1

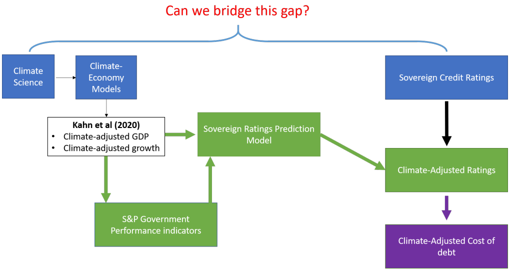


This figure shows the current rating assigned to our country-year observations (x-axis) and the out-of-sample estimated rating from our model (y-axis). Proximity to the black line indicates greater accuracy in our model.

2. Model accuracy 2

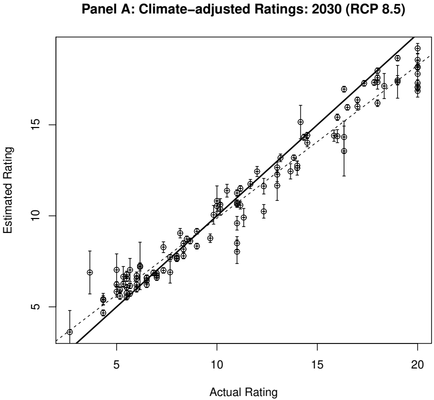


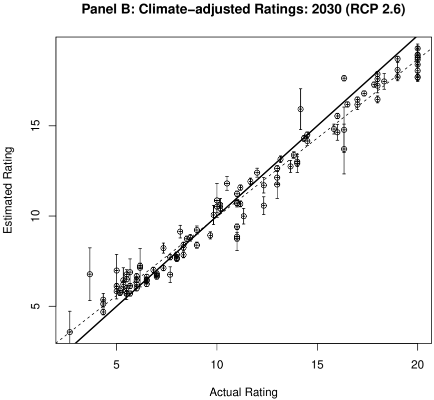
2. Putting it together



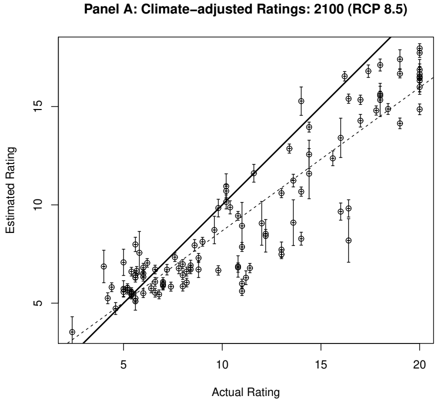
- Predict ratings using our model and climate-adjusted variables
- Using three warming scenarios
  - RCP 2.6
  - RCP 8.5
  - RCP 8.5 with increasing temperature variability

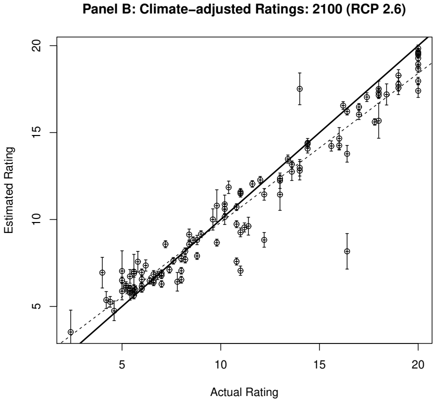
3. Results 1: 2030 projections



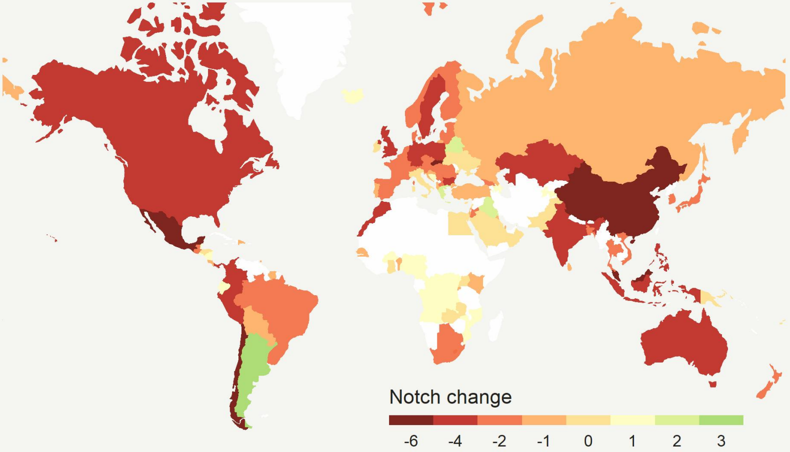


3. Results 2: 2100 projections



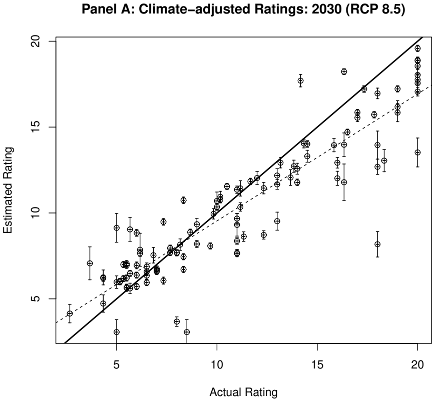


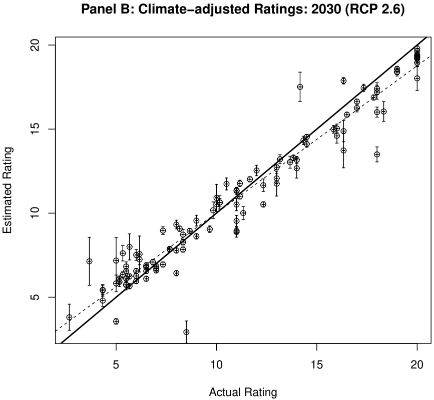
3. Results 3: 2100 projections - RCP 8.5



The range of notch changes is from -8 to +3, the legend indicates intervals

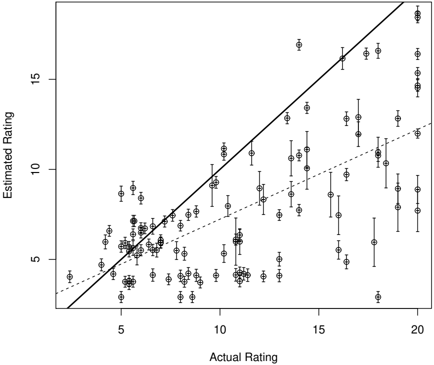
3. Results 4: 2030 projections with temperature volatility



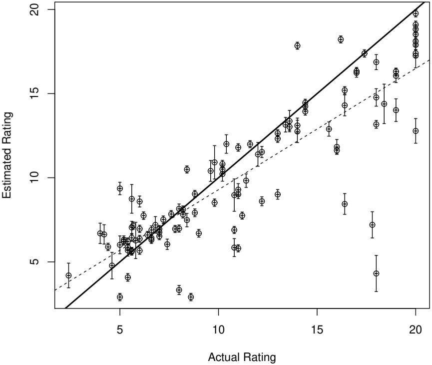


3. Results 5: 2100 projections with temperature volatility

Panel A: Climate–adjusted Ratings: 2100 (RCP 8.5)



Panel B: Climate–adjusted Ratings: 2100 (RCP 2.6)



3. Climate-induced increases in costs of sovereign debt (2100)

Scenario	Sample	Outstanding debt	Climate-induced down-grades	Additional cost of debt (lower)	Additional cost of debt (upper)
RCP 2.6	G7	33,617.8	0.58	14.1	21.2
	Full sample	42,716.8	0.65	22.8	34.1
RCP 8.5	G7	35,843.1	3.16	101.1	151.6
	Full sample	47326.7	2.48	136.8	205.1

4. Summary

- Primary focus is to stay as true to the climate science as possible
- Paris commitments will reduce downgrades
- Delaying green investment increases future cost