Apocalypse Now? Projecting CO2 Emissions with Neural Networks

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Setting the scene

- **What**: We project CO_2 emissions through 2100 using a *reduced-form model* and scenarios for per capita GDP from the Shared Socioeconomic Pathways (SSPs)
- **Why**: Scenario-based CO_2 emissions projections help determine if current climate policies are sufficient for reaching policy goals like those of the Paris Agreement
- **How**: We extend the methodology developed by Bennedsen et al. (2021) and propose a novel panel data model that combines country fixed effects with a long short-term memory (LSTM) recurrent neural network regression component

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A supplement to integrated assessment models

- Often, *large-scale structural models* known as integrated assessment models (IAMs) are used to make scenario-based emissions projections
  - They rely on a large number of structural and parametric assumptions
  - Parameter values are typically set using a mixture of judgment and calibration
- Our reduced-form emissions projections reflect a *change-as-usual* assumption and provide a historical benchmark against which IAM projections can be compared
  - They rely on a neural network representation of the per capita GDP-CO_2 relationship
  - Parameter values are estimated using yearly data on 187 countries for 1960-2018

Research question

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Are scenario-based emissions projections from structural IAMs consistent with reduced-form emissions projections that reflect historical experience?

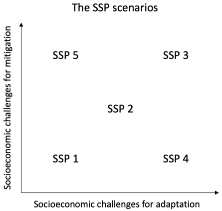
Methodological contribution

We combine country fixed effects with an LSTM recurrent neural network; we account for time *implicitly* by letting predictions depend on the income path of a country

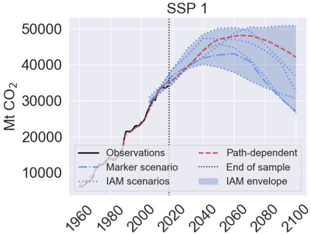
Empirical contribution

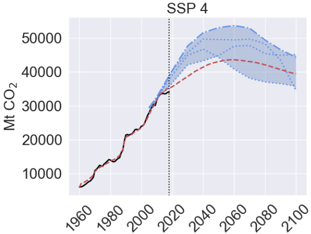
We consider the novel SSP scenarios also used in the latest IPCC report (IPCC, 2021)

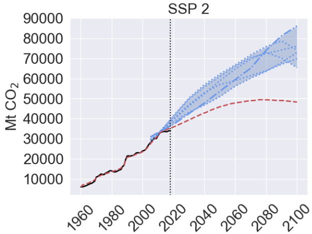
Global baseline projections

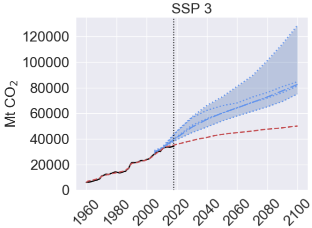


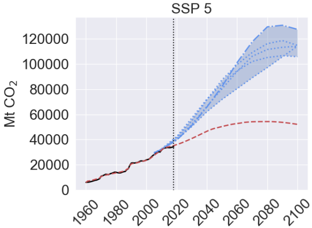
Source: Adapted from Dellink et al. (2017)











Conclusion and future research

- We propose a novel panel data model that combines country fixed effects with a long short-term memory (LSTM) recurrent neural network regression component
- For scenarios with low socioeconomic challenges for mitigation (SSP1 and SSP4), our emissions projections appear consistent with baseline projections from IAMs
- For scenarios with medium and high socioeconomic challenges for mitigation (SSP2, SSP3, and SSP5), our emissions projections appear the most consistent with mitigation projections from IAMs that target a forcing of 6.0 W/m^2 by 2100
- We are currently working on the construction of uncertainty estimates

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The problem of explicit time dependence

Reduced-form panel data models previously considered for scenario-based emissions projections depend *explicitly* on time and thus cannot be readily used out-of-sample:

- Quadratic model: $y_{it} = \alpha_i + \beta_t + \delta_1 x_{it} + \delta_2 x_{it}^2 + \nu_{it}$
  - Holtz-Eakin and Selden (1995); Zhao and Du (2015)
- Spline-based model: $y_{it} = \alpha_i + \beta_t + f^{\text{spline}}(x_{it}) + \nu_{it}$
  - Schmalensee et al. (1998)
- i, t index, respectively, countries and time periods
- $y_{it}, x_{it} \in \mathbb{R}$ are the natural log of, respectively, per capita emissions and GDP
- $\nu_{it} \in \mathbb{R}$ is an error term

The path-dependent neural network model

We propose a path-dependent neural network model that depends *implicitly* on time:

$$y_{it} = \alpha_i + \phi(r)^\top z_{it}^{(h)} + \nu_{it}, \qquad i = 1, \dots, N_t; \;\; t = 1, \dots, T \tag{1}$$

$$z_{it}^{(h)} = \mathcal{H}^{(h)}(z_{it}^{(h-1)}, z_{it-1}^{(h)}) \tag{2}$$

$$\vdots$$

$$z_{it}^{(2)} = \mathcal{H}^{(2)}(z_{it}^{(1)}, z_{it-1}^{(2)}) \tag{3}$$

$$z_{it}^{(1)} = \mathcal{H}^{(1)}(x_{it}, z_{it-1}^{(1)}) \tag{4}$$

- $y_{it}, x_{it} \in \mathbb{R}$ are the natural log of, respectively, per capita emissions and GDP
- r is a regional indicator; we initially map each country to one of five regions
- $z_{it}^{(\ell)} \in (-1,1)^{q_\ell}$, $\ell = 1, \dots, h$, is a column vector of derived variables
- Hidden layer functions $\mathcal{H}^{(\ell)}$ are implemented using LSTM layers

Long short-term memory (LSTM) layer

Hidden layer functions $\mathcal{H}^{(\ell)}$, $\ell = 1, \dots, h$, are implemented using LSTM layers through the following composite function:

$$z_{it}^{(\ell)} = o_{it}^{(\ell)} \odot \tanh(s_{it}^{(\ell)}) \tag{5}$$

$$s_{it}^{(\ell)} = f_{it}^{(\ell)} \odot s_{it-1}^{(\ell)} + g_{it}^{(\ell)} \odot \tanh\left(\kappa_s^{(\ell)} + \Gamma_{z^{(\ell-1)}s}^{(\ell)} z_{it}^{(\ell-1)} + \Gamma_{z^{(\ell)}s}^{(\ell)} z_{it-1}^{(\ell)}\right) \tag{6}$$

$$f_{it}^{(\ell)} = \sigma\left(\kappa_f^{(\ell)} + \Gamma_{z^{(\ell-1)}f}^{(\ell)} z_{it}^{(\ell-1)} + \Gamma_{z^{(\ell)}f}^{(\ell)} z_{it-1}^{(\ell)}\right) \tag{7}$$

$$g_{it}^{(\ell)} = \sigma\left(\kappa_g^{(\ell)} + \Gamma_{z^{(\ell-1)}g}^{(\ell)} z_{it}^{(\ell-1)} + \Gamma_{z^{(\ell)}g}^{(\ell)} z_{it-1}^{(\ell)}\right) \tag{8}$$

$$o_{it}^{(\ell)} = \sigma\left(\kappa_o^{(\ell)} + \Gamma_{z^{(\ell-1)}o}^{(\ell)} z_{it}^{(\ell-1)} + \Gamma_{z^{(\ell)}o}^{(\ell)} z_{it-1}^{(\ell)}\right) \tag{9}$$

- $z_{it}^{(\ell)}, s_{it}^{(\ell)}, \in (-1,1)^{q_\ell}$, $f_{it}^{(\ell)}, g_{it}^{(\ell)}, o_{it}^{(\ell)} \in (0,1)^{q_\ell}$ are column vectors
- $\sigma(z) = (1 + \exp(-z))^{-1}$ for $z \in \mathbb{R}$

Estimation

We estimate all parameters simultaneously by minimizing a global mean squared error loss function where errors are based on the levels of emissions:

$$J(\phi, \kappa, \Gamma, \alpha) = \sum_{r=1}^{R} \sum_{t=1}^{T} \sum_{i \in I_r} \frac{1}{n} \left(\left[e^{y_{it}} - e^{\hat{y}_{it}(x_{it})} \right] \times \text{POP}_{it} \right)^2$$

- $I_r \subseteq \{1, 2, \ldots, N\}$ is the set of indices of countries belonging to region r
- $\hat{y}_{it}$ is model output dependent on x_{it} and estimated parameter $\hat{\phi}, \hat{\kappa}, \hat{\Gamma}, \hat{\alpha}$
- POP_{it} is the population size
- n is the total number of observations across countries

Model selection

We use the Bayesian information criterion (BIC) to select the network architecture (i.e. the number of layers h and the widths $q_1, \ldots, q_h$):

$$\text{BIC} = \log J(\hat{\phi}, \hat{\kappa}, \hat{\Gamma}, \hat{\alpha}) + \frac{m \log n}{n}$$

- $J(\hat{\phi}, \hat{\kappa}, \hat{\Gamma}, \hat{\alpha})$ is the loss function evaluated in parameters estimates
- m is the total number of model parameters excluding fixed effects
- n is the total number of observations across countries

Data set

For estimation, we use an unbalanced panel of data with yearly observations on 187 countries on the following variables for the period 1960-2018:

- CO_2 emissions,[1] megatonnes (10^6 tonnes)
- GDP,[2] billion 2005 U.S. dollars adjusted using purchasing power parities
- Population,[3] millions

The data set contains 8,641 observations

[1] Territorial CO_2 emissions estimates are from the Global Carbon Project (2019)
[2] GDP data is from `databank.worldbank.org/source/world-development-indicators`
[3] Population data is from `databank.worldbank.org/source/world-development-indicators`

Region definitions

To allow the effect of being on a given income path to differ across regions, we consider the five macro-regions defined for the SSPs (Riahi et al., 2017):

- OECD: 41 OECD90 and EU member states and candidates
- REF: 13 reforming economies of Eastern Europe and the Former Soviet Union
- Asia: 35 Asian countries excluding the Middle East, Japan and Former Soviet Union states
- MAF: 64 countries of the Middle East and Africa
- LAM: 34 countries of Latin America and the Caribbean

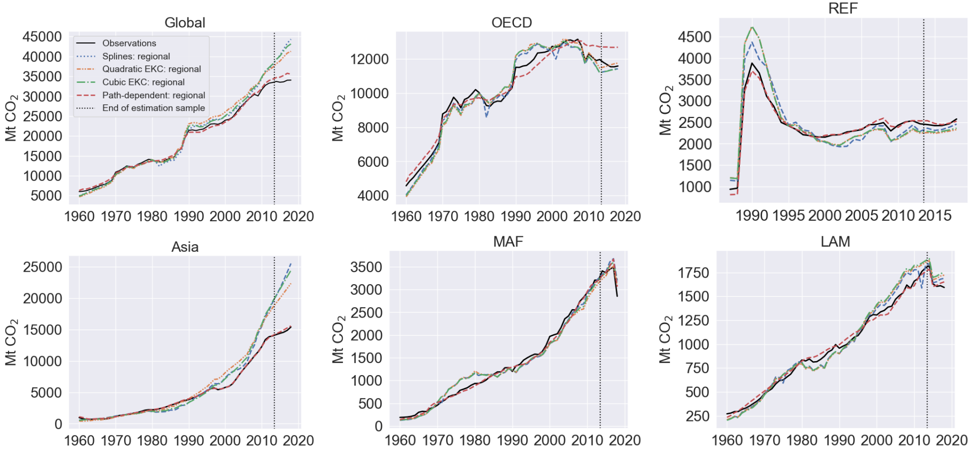
Out-of-sample setup

- We split the data: *estimation sample* (1960-2013) and *test sample* (2014-2018)
- We construct *conditional predictions* using the relation:

$$\hat{Y}_t = \sum_{r=1}^{R} \sum_{i \in I_r} e^{\hat{y}_{it}(x_{it})} \times \mathrm{POP}_{it}, \qquad t = 2014, 2015, \ldots, 2018$$

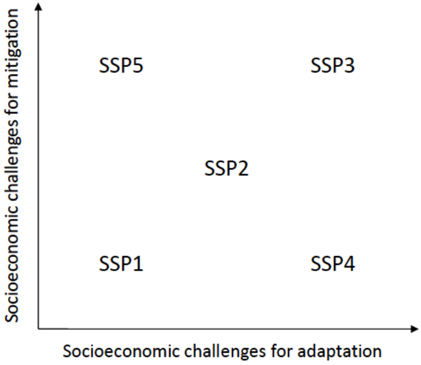
  - $\hat{y}_{it}$ is model output (a prediction of the log transformation of per capita emissions)
  - For each country separately, we build memory by pre-appending the data from the estimation sample to the data from the test sample
- Three benchmarks: a quadratic model, a cubic model, and a spline-based model
  - Estimated time fixed effects for 2013 are used for out-of-sample predictions
  - Benchmark models are estimated region-by-region

Out-of-sample predictions



The Shared Socioeconomic Pathways (SSPs)

- **Five main scenarios** for national-level GDP, population, and urbanization, together with qualitative assumptions on the energy and land-use sectors
- **First axis**: factors that increase risks associated with climate change
- **Second axis**: factors that lead to higher reference emissions in absence of new climate policy, and factors that reduce mititgative capacity of society



Source: Adapted from Dellink et al. (2017)

The SSP scenario matrix framework

Forcing[4] (W/m^2)	SSP1	SSP2	SSP3	SSP4	SSP5
Baseline	SSP1-Base	SSP2-Base	SSP3-Base	SSP4-Base	SSP5-Base
6	NA	SSP2-60	SSP3-60	SSP4-60	SSP5-60
4.5	SSP1-45	SSP2-45	SSP3-45	SSP4-45	SSP5-45
3.4	SSP1-34	SSP2-34	SSP3-34	SSP4-34	SSP5-34
2.6	SSP1-26	SSP2-26	NA	SSP4-26	SSP5-26
1.9	SSP1-19	SSP2-19	NA	NA	SSP5-19

Source: Adapted from Riahi et al. (2017)

[4] Anthropogenic radiative forcing is a measure of the human contribution to climate change. Specifically, it measures the net change in the energy balance of the Earth system due to human activities relative to pre-industrial levels, expressed in watts per square meter (W/m^2)

Scenario projections setup

- We make projections through 2100 using national-level scenarios for per capita GDP from the SSP *main scenarios*:

$$\hat{Y}_t = \sum_{r=1}^{R} \sum_{i \in I_r} e^{\hat{y}_{it}(x_{it})} \times \mathrm{POP}_{it}, \qquad t = 2019, 2020, \ldots, 2100$$

- To ensure robustness, we estimate the model ten times using different initializations, then average the projections
- We compare our reduced-form model projections to baseline and mitigation projections from multiple different IAMs[5]

[5] Downloaded from `tntcat.iiasa.ac.at/SspDb` on July 9, 2021

Global mitigation projections