Investigating the GDP-CO_2 relationship using a neural network approach

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Environmental Kuznets Curve (EKC)

The EKC hypothesis postulates and inverse U-shaped relationship between per capita GDP and per capita CO_2 emissions.

- Traditional explanations for the EKC hypothesis:
  - Scale effect
  - Composition effect
  - Technique effect
- Trade-related explanation for the EKC hypothesis:
  - Displacement effect

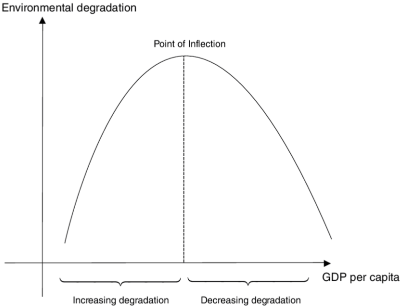


Fig. 3.3 of Mcneill et al. (2011)

Research Questions

1. We examine the shape of the GDP-CO_2 relationship at a global level and at the level of five large regions of the world, using a neural network approach.
2. We examine the importance of the displacement effect using territorial emissions and consumption-based emissions.
3. We project CO_2 emissions into the future using the Shared Socioeconomic Pathways.

Related literature:

- Parametric approaches: Grossman and Krueger (1991); Holtz-Eakin and Selden (1995).
- Semiparametric approaches: Schmalensee et al. (1998); Millimet et al. (2003); Auffhammer and Steinhauser (2012).

Standard Methodology I

- The generic EKC regression model:

$$y_{it} = \kappa + f\left(x_{it}\right) + u_{it}, \qquad i = 1, \ldots, N_t; \; t = 1, \ldots, T,$$
$$u_{it} = \alpha_i + \beta_t + \nu_{it}.$$

  - y_{it} is the natural logarithm of per capita CO_2 emissions.
  - x_{it} is the natural logarithm of per capita GDP.

- In the literature, it is standard to treat α_i and β_t as fixed effects and impose the parametric assumption that $f(x_{it}) = \delta_1 x_{it} + \delta_2 x_{it}^2$.

Standard Methodology II

- The standard EKC regression model likely suffers from econometric problems pertaining to omitted variable bias, integrated variables and spuriousness and functional **misspecification** (Wagner, 2015; Stern, 2017).
- We focus on the misspecification issue and represent $f(\cdot)$ using a **neural network** architecture, which are known to have universal approximation capabilities (e.g. Cybenko, 1989).

Proposed Methodology

We propose an augmented feedforward neural network model:

$$y_{it} = \sum_{j=2}^{N} \alpha_j d_{j,it} + \sum_{s=2}^{T} \beta_s d_{s,it} + \delta^\top z_{it} + \nu_{it},$$

$$z_{it} = g\left(\gamma_0 + x_{it}\gamma_1\right).$$

- y_{it} is the natural logarithm of per capita CO_2 emissions.
- x_{it} is the natural logarithm of per capita GDP.

- $d_{j,it} = \mathbb{1}_{\{i=j\}}$ and $d_{s,it} = \mathbb{1}_{\{s=t\}}$ specify country and time dummy variables.
- $z_{it} \in \mathbb{R}^q$ is a vector of derived variables, where q is referred to as the number of hidden units. We use $q = 8$ throughout.
- $g(a) = a\left(1 + \exp(-a)\right)^{-1}$ is applied elementwise, referred to as the Swish activation function (Ramachandran et al., 2017).

Partial Simulation Results

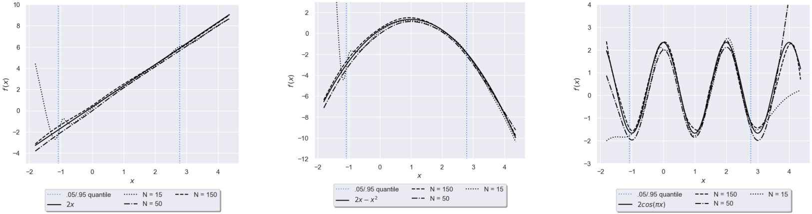


Figure: Balanced panel

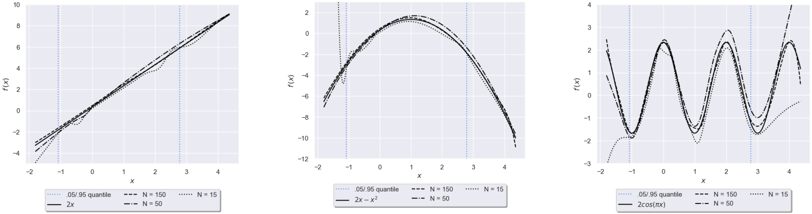


Figure: 50pct. randomly missing data

Main Takeaway from Simulation Study

Considering a realistic simulation setup;

- 50 time periods,
- a varying number of cross-sectional units (countries),
- country-specific stochastic trends,
- missing data,

our proposed methodology is able to

- recover various functional forms of different complexity,
- perform well in case of missing data,
- perform well when relying only on few cross-sectional units.

Note: We indicate the .05/.95 quantiles, as the high degree of flexibility of the neural network model component suggests that the estimated functional form should not be trusted much outside the region where the model has seen a lot of data during estimation.

Data

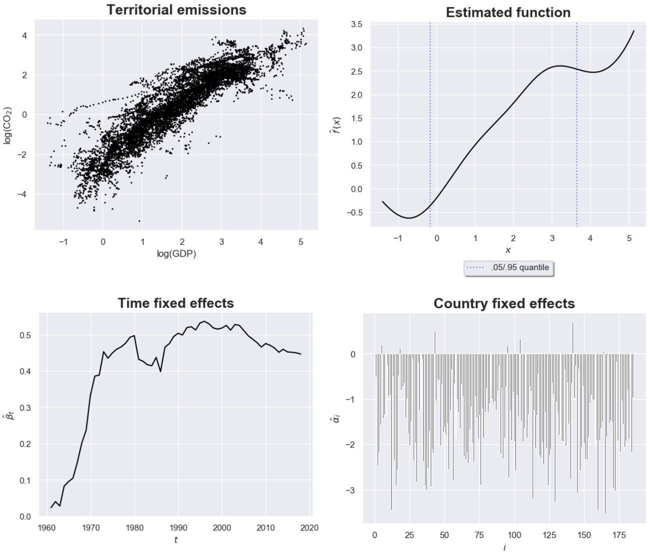
- Data on GDP, population, PPP conversion factor and the GDP deflator is from the World Development Indicators database of the World Bank[1].
- Two types of emissions from Global Carbon Project (2018):
  1. Territorial CO_2 emissions.
  2. Consumption-based CO_2 emissions.

Note: consumption-based CO_2 emissions = territorial emissions + emissions from imports - emissions from exports.

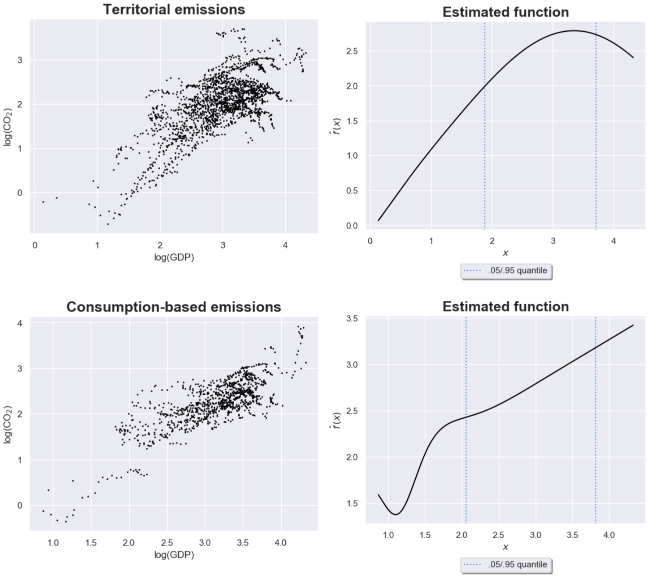
$\Rightarrow$ Unbalanced panel of per capita GDP in 2005 USD (PPP) and per capita CO_2 emissions for 186 countries covering 1960-2018.

[1] Accessible at https://databank.worldbank.org/source/world-development-indicators

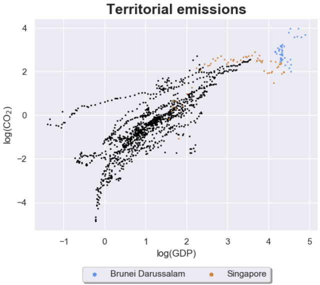
World

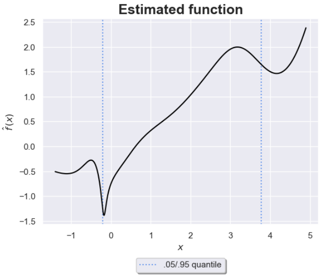

Territorial emissions
log(CO$_2$)
log(GDP)
Estimated function
$\hat{f}(x)$
x
.05/.95 quantile
Time fixed effects
$\hat{\beta}_t$
t
Country fixed effects
$\hat{\alpha}_i$
i

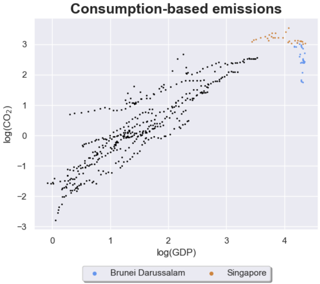
OECD

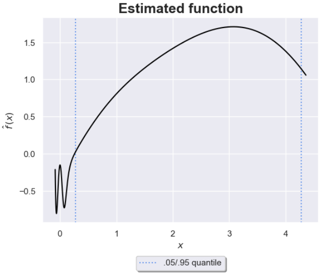

Territorial emissions
log(CO2)
log(GDP)
Estimated function
$\hat{f}(x)$
x
.05/.95 quantile
Consumption-based emissions
log(CO2)
log(GDP)
Estimated function
$\hat{f}(x)$
x
.05/.95 quantile

Asia


Territorial emissions
log(CO2)
log(GDP)
Brunei Darussalam
Singapore


Estimated function
$\hat{f}(x)$
x
.05/.95 quantile


Consumption-based emissions
log(CO2)
log(GDP)
Brunei Darussalam
Singapore


Estimated function
$\hat{f}(x)$
x
.05/.95 quantile

Main Takeaway from In-sample Analysis

- We find evidence of a world EKC relationship.
- We find evidence of an EKC relationship for OECD.
  - Relationship appears to be driven by the displacement effect.
- We find some evidence of an EKC relationship for Asia.
  - Relationship appears not to be driven by the displacement effect.
- We find evidence of a linear GDP-CO_2 relationship for the regions REF[2], MAF[3] and LAM[4] (not included in slides).

[2] Reforming Economies of Eastern Europe and the Former Soviet Union.

[3] Middle East and Africa.

[4] Latin America and the Caribbean.

Shared Socioeconomic Pathways (SSPs)

- We project CO_2 emissions through 2100, using as input scenario data from the SSP database[5].
- As benchmark, we use **emissions** projections from integrated assessment (IAM) models[6].

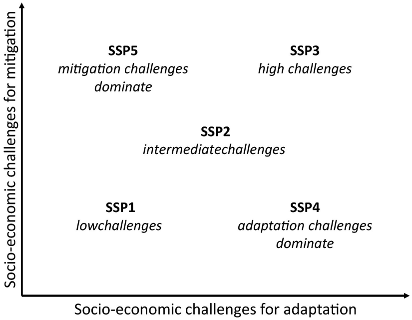


Fig. 1 of Dellink et al. (2017)

[2] The SSPs provide five distinct pathways of future developments in the absence of additional climate policies, and contain quantified population and GDP trajectories (available at a country-level through 2100). The SSPs are also the scenarios used by the Intergovernmental Panel on Climate Change for their next report due to be published in 2021-2022. The SSP data is accessible at https://tntcat.iiasa.ac.at/SspDb.

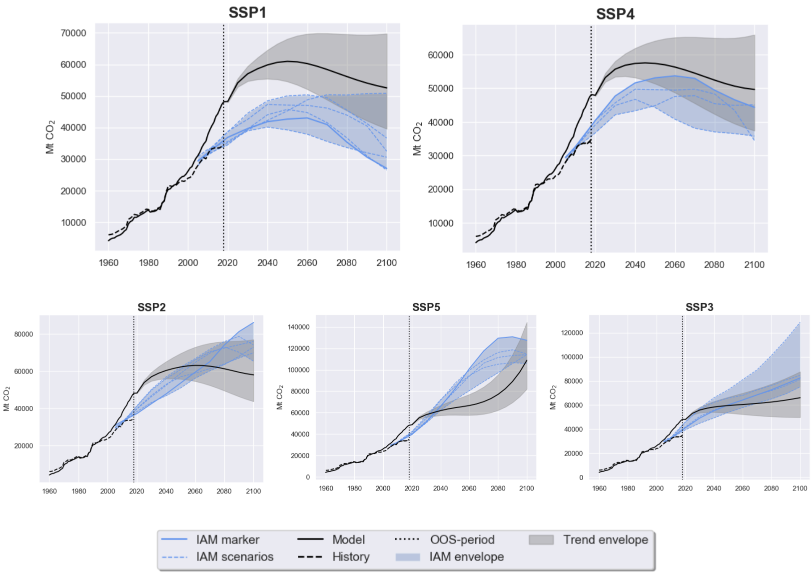
[3] Available through the SPP database.

Extrapolating Time Effects Into the Future (WIP)

We follow the approach of Holtz-Eakin and Selden (1995):

1. We fix the time-specific effect at its estimated level in the last year of the sample (2018).
2. We assume that the time-specific effect by 2100 is, alternatively, higher or lower by an amount equal to two standard deviations of the estimated time-specific effects.
   - Intervening years are assumed to adjust linearly.

Future Projections (WIP)



Conclusion/Outlook

- We find evidence of an EKC relationship for the world, OECD and Asia, but not for the regions REF, MAF and LAM.
- The displacement effect appears to be important for explaining the observed EKC relationship for OECD.
- The most optimistic CO_2 emissions scenarios of the climate change community (SSP1 and SSP4) are somewhat below what we project.
- We are currently working on improving the aggregate in-sample fit of our methodology, potentially by losing the assumption of additive time-specific effects, and allowing the shape of the GDP-CO_2 relationship to change over time.
- We are currently working on optimal ways of choosing the smoothing parameter of our methodology, q, potentially by using information criteria.

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