EXTRAPOLATED TRENDS VERSUS ENERGY MODEL PROJECTIONS – GLOBAL DISTRIBUTION DYNAMICS DERIVED FROM REGIONAL KAYA DECOMPOSITION

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Overview

The development of economic growth, energy demand, and environmental quality are key inputs to design policy options for a global sustainable development. Future scenarios produced by energy system models and integrated assessment models can provide useful insights into future pathways but they cannot be validated. We apply the method of distribution dynamics to historical data as an alternative projection method and as a way to analyze and test scenario output produced for the Global Energy Assessment Report, GEA (2012), the World Energy Outlook 2015, as well as for the Global Energy and Climate Outlook, Labat et al. (2015). More specifically, we look into the evolution of cross-country/regional patterns appearing in the factors of the Kaya decomposition.
The paper is structured in the following way. First, we briefly review the method of distribution dynamics and we show how the distribution functions we have selected are related to Kaya's identity. The main section than compares the trend analysis of historical data with the projected patterns for the global distributions of the Kaya factors. To this end, an ergodic distribution is determined to estimate the behavior in the far future. A summary and outlook concludes the paper.

Methods

We generalize the Kaya decomposition of the global CO2 emissions to account for the regional distribution of the drivers by representing the emissions as

$$CO_2(t) = \sum_i CO_{2,i}(t) = POP(t) \times \sum_i e_i(t) \times f_i(t) \times g_i(t) \times p_i(t)$$

where for each region *i* we have carbon dioxide emissions per final energy e_i, final energy per GDP f_i, GDP per population g_i, and p_i being the share of regional population in world population POP. Following ideas from density estimation theory, this expression is reinterpreted as the population-weighted expectation value of a trivariate joint probability function *f*

$$CO_2(t) \quad = \quad POP(t) \int dxdydz\, xyz\, f(x,y,z;t)$$

which is given by a kernel density estimate as

$$f(x,y,z) \quad = \quad \frac{1}{h_x h_y h_z} \sum_i p_i K\left(\frac{x-e_i}{h_x}\right) K\left(\frac{y-f_i}{h_y}\right) K\left(\frac{z-g_i}{h_z}\right).$$

Here, K is the so called kernel function, which is assumed to be normalized with vanishing first moment. For a smooth estimation of the unknown distribution function *f* of the sampled data, a proper choice of the bandwidth parameter h_x, h_y, h_z is essential, see Silverman (1986). To this end, we adapt data-driven bandwidth selection rules given in the literature to our situation, cf. Goerlich Gisbert (2003) and Wang, Wang (2007). In principle, the probability function *f* can by projected into the future by a Markov process, where the transition function is modelled from historical data. In this way, trends in the evolution of the distribution function are propogated to obtain a prediction for the individual distribution of GDP per capita etc. and the joint function *f*. In contrast to traditional methods, where only mean values and/or moments of the distribution are extrapolated, such an approach estimates the distribution function as a whole. In particular, the propagation into the far future can serve as a means to study if regional disparities converge or not. These distributions can be compared with kernel density estimates for regional data generated by baseline scenarios in energy system models. In a first step, we implement this approach for the univariate regional distribution of carbon intensity, final energy intensity and per capita GDP. Having these quantities at our disposal, we propagate the trivariate joint distribution function, which is a difficult task in itself. We use a copula representation of distribution functions to connect the trivariate distribution to its univariate marginal distributions and to bivariate distribution functions, see Trivedi (2007). As a result, we obtain a prediction for carbon emissions extrapolating trends from a time period given by historical data.

Results

The added value of our paper is three-fold: first, we analyze projected energy transformation pathways focusing on the development of regional disparities in the world. This adds to the discussion of WEO, GEA and GECO results, because these studies look more into global results or that of specific regions. Second, we suggest a method that can be used to analyze the development of projected regional disparities in contrast to what has been observed in history. This can support testing models which are per-se impossible to validate ex-ante (c. f. Schwanitz (2013)). Third, we contribute to the growing literature on distribution dynamics by widening its application beyond the study of income or final intensity distributions. We also propose a new bandwidth selection rule for weighted samples.

Conclusions

We find that the projected future economic development of baseline scenarios is biased towards convergence whereas energy demand patterns across world regions unfold smoothly from historical data and are close to the alternative projection that we derive from the ergodic distribution. The development of carbon intensity of final energy is strongly prescribed by regional frameworks. This global distribution seems unlikely to converge.

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