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Employing the Shared Socioeconomic Pathways to Predict CO_2 Emissions

Tobias Böhmelt*

ETH Zürich
Center for Comparative and International Studies
Haldeneggsteig 4
8092 Zürich
Switzerland

University of Essex
Department of Government
Wivenhoe Park
Colchester CO4 3SQ
United Kingdom

tbohmelt@essex.ac.uk

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Abstract

Predicting CO_2 emissions is of significant interest to policymakers and scholars alike. The following article contributes to earlier work by using the recently released "shared socioeconomic pathways" (SSPs) to empirically model CO_2 emissions in the future. To this end, I employ in-sample and out-of-sample techniques to assess the prediction accuracy of the underlying model, before forecasting countries' emission rates until 2100. This article makes three central contributions to the literature. First, as one of the first studies, I improve upon the Representative Concentration Pathways (RCPs) by incorporating the SSPs, which did not exist when the RCPs have been released. Second, I calculate predictions and forecasts for a global sample in 1960-2100, which circumvents issues of limited time periods and sample selection bias in previous research. Third, I thoroughly assess the prediction accuracy of the model, which contributes to providing a guideline for prediction exercises in general using in-sample and out-of-sample approaches. This research presents findings that crucially inform scholars and policymakers, especially in light of the prominent 2 °C goal: *none* of the five SSP scenarios is likely to be linked to emission patterns that would suggest achieving the 2 °C goal is realistic.

Keywords: CO_2 Emissions, Forecasting, In-Sample Prediction, Out-of-Sample Prediction, Shared Socioeconomic Pathways

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1 Introduction

The Conference of the Parties (COP) of the United Nations Framework Convention on Climate Change (UNFCCC) has institutionalized and firmly implemented the so-called "2 °C goal." Initially suggested in the mid-1990s, according to this target, the world community seeks to limit global average temperature rise to within 2 °C (e.g., Jordan et al., 2013; Field et al., 2014). Any change in the climate associated with a temperature rise higher than 2 °C is seen as "dangerous," and mitigation and adaptation strategies as well as short-term and medium-term goals for policymakers are largely based on this threshold (Jordan et al., 2013, p.751). The reduction in carbon dioxode (CO_2) emissions constitutes a central pillar for these goals and strategies to meet the 2 °C target: according to the Intergovernmental Panel on Climate Change (IPCC) (Field et al., 2014), CO_2 emissions should not exceed 1,000 gigatons (Gt) by 2100 if the risk of *not* meeting the 2 °C goal should not be higher than 33 percent. In light of this, the IPCC (Field et al., 2014) also estimates that 748.2 Gt would be emitted by 2030, and significant reductions in countries' CO_2 rates would be necessary afterwards for not exceeding 1,000 Gt by 2100.

But how likely is it that this target will be achieved? Is it realistic to assume that countries would not pass 1,000 Gt of CO_2 emissions by 2100 and is it possible that emissions will decline around 2030? Jackson et al. (2015), for example, highlight that emission rates have not increased in the past few years, while Le Quéré et al. (2016, p.607) state that the growth in emissions "was approximately zero" in 2015. This may not necessarily suggest that emissions have peaked, and initial estimates of Le Quéré et al. (2016, p.607) also show that there was a slight growth in 2016. However, and the latter observation underlines this, for thoroughly addressing these and related issues, policymakers and scholars require accurate predictions of carbon emission development. Predictions not only allow to get a better informed idea about possible scenarios that may emerge in the future, but also help estimating expected costs of emission reductions, calculating potential benefits from preventing global warming, and identifying whether more effective and stringent climate policy measures are necessary (e.g., Ward, Greenhill and Bakke, 2010; Zhao and Du, 2015). In the words of Riahi et al. (2017, p.154), projections "help us to understand long-term consequences of near-term decisions, and enable researchers to explore different possible futures in the context of fundamental future uncertainties."

To this end, if predictions tell us that it becomes increasingly unlikely to meet the 2 °C goal if current emission patterns were to continue, the global community must strengthen and extend its policies. Information on the likely future levels of emission behavior is necessary to arrive at reasonable conclusions. It is therefore not surprising that a considerable body of literature focuses on predicting CO_2 emissions, both within and "outside" the IPCC (e.g., Van Vuuren et al., 2011; Field et al., 2014; Zhao and Du, 2015; Pérez-Suárez and López-Menéndez, 2015; Le Quéré et al., 2016; Riahi et al., 2017). The next section discusses these studies in detail, but it is important to note already here that their results are generally mixed: depending on the underlying assumptions about key predictors, emissions may increase, decrease, or not change much at all until 2100. For example, Zhao and Du (2015) mainly focus on Organization for Economic Cooperation and Development (OECD) countries in the post-1997 period and predict that CO_2 emissions will decrease by 25 percent by 2050. Pérez-Suárez and López-Menéndez (2015) analyze a global sample of states and forecast that some countries may increase their emissions until 2020, but others may not. Finally, the arguably most prominent study on emission predictions as it is also part of the last IPCC report, the Representative Concentration Pathways (RCPs), identified four future scenarios for how emissions will develop until 2100. In three out of these four scenarios, CO_2 emissions are likely to rise at least until 2080; and even then, an eventual decline may not occur.

The following article seeks to contribute to this debate by using the recently released "shared socioeconomic pathways" (SSPs) (Kriegler et al., 2012; O'Neill et al., 2014; O'Neill et al., 2017; Hegre et al., 2016; Riahi et al., 2017) for the prediction and forecast of CO_2 emissions until 2100. The SSPs are based on historical data and future projections of *inter alia* three key variables: population, GDP per capita, and the proportion of young males with upper secondary schooling or higher. With these variables, the SSPs identify five different scenarios for the future and, most importantly, capture low and high barriers to adaptation and mitigation to climate change:[1] SSP1 (sustainability), SSP2 ("middle of the road"), SSP3 (fragmentation), SSP4 (inequality), and SSP5 (conventional development). I thus answer the call of the IPCC Scenario Process for AR5 that stated: "[n]ew sets of scenarios for climate change research are needed periodically to take into account scientific advances [...]."[2] And I follow Riahi et al. (2017, p.165) in that I build on the "starting point for new climate change assessments through the lens of the SSPs and the new scenario framework." Needless to say, predictions and forecasts involve by definition some degree of uncertainty and depend on several assumptions, including an appropriate baseline model, and they can hardly account for random events. I believe, however, that this research makes several contributions to the literature and is likely to crucially inform policymakers (see also Hegre et al., 2013, pp.250-251).

First, as one of the first studies (as an exception, see Riahi et al., 2017), I improve upon the RCPs by incorporating the SSPs, which did not exist when the RCPs have been released. On one hand, the scenarios used for the RCPs are not decoupled from the physical processes associated with climate change, which might pose problems in terms of endogeneity. On the other hand, the underlying assumptions about socio-economic trajectories and priorities are not consistent between the RCPs (Van Vuuren et al., 2011). In fact, "scenario development after the RCP phase will focus on developing a new set of socio-economic scenarios" (Van Vuuren et al., 2011, p.16). And, finally, the SSPs directly take into account policy decisions in that they are based on different mitigation and adaptation strategies (for an overview, see

[1] In fact, "each pathway is defined in terms of challenges to climate change mitigation and adaptation" (Hegre et al., 2016, p.2). See also O'Neill et al. (2017) and Riahi et al. (2017) for a detailed overview.

[2] Moreover, Van Vuuren et al. (2011, p.28) emphasize that "subsequent phases of the development process of new scenarios for climate change assessment need to focus on defining a framework for *socio-economic assumptions and storylines* to guide RCP-based mitigation, adaptation, and impacts analyses" (emphasis added).

Riahi et al., 2017). Second, I calculate predictions and forecasts for a global sample in 1960-2100. Earlier work predominantly focuses only on a subset of states, short time periods, or a combination of both. My approach circumvents issues of limited time periods and sample selection bias in previous research. Finally, I thoroughly assess the prediction accuracy of the underlying model, which is hardly done in earlier works. Pérez-Suárez and López-Menéndez (2015) or Pao and Tsai (2011) are a few exceptions that explicitly discuss the accuracy of their predictions, but this seems to be the exception rather than the norm. Eventually, I therefore may also contribute to providing a guideline for prediction exercises in general using in-sample and out-of-sample techniques and to the debates on the validity of policies based on empirical models on states' behavior (see, e.g., Choucri and Robinson, 1978; Goldstone et al., 2010; O'Brian, 2010; Schneider, Gleditsch and Carey, 2010, 2011; Ward, Greenhill and Bakke, 2010; Bueno de Mesquita, 2011; Gleditsch and Ward, 2013). To the best of my knowledge, Riahi et al. (2017) is the only existing study that combines the SSPs with a CO_2 emission prediction exercise. I built upon that work by introducing a more parsimonious model, assessing the prediction accuracy, and thereby examining the consistency of results.

In a first step, I examine the predictive power of a model based on the SSPs via in-sample and out-of-sample techniques. The in-sample approach focuses on a global sample of states in 1960-1995, while the out-of-sample methods look at the period from 1960 to 2014, but treat 1996-2014 as if unobserved. I also consider a 4-fold cross-validation exercise for assessing the out-of-sample power of the predictions (see Ward, Greenhill and Bakke, 2010), before forecasting emission patterns for the five SSPs until 2100. This research presents findings that crucially inform scholars and policymakers, especially in light of the prominent 2 °C goal: *none* of the five SSP scenarios is likely to be linked to emission patterns that would suggest that achieving the 2 °C goal is realistic. Hence, without future adjustments, it is unlikely that the world community will meet the 2 °C goal; this is consistent with other prominent projection studies.

2 Determinants of CO_2 Emissions

2.1 Previous Literature

There is a large body of literature in the social and environmental sciences analyzing the determinants of countries' CO_2 emissions and, more generally, environmental performance at the outcome level (e.g., Congleton, 1992; Li and Reuveny, 2006; Ward, 2006, 2008; Bättig and Bernauer, 2009; Bernauer and Koubi, 2009; Fiorino, 2011; López, Galinato and Islam, 2011; Spilker, 2012; Bernauer and Böhmelt, 2013*a*; Bernauer and Koubi, 2013; Liao and Cao, 2013; Spilker, 2013; López and Palacios, 2014; Böhmelt, Böker and Ward, 2015; Cao and Ward, 2015). This literature usually focuses on a set of political, economic, and demographic factors at the domestic, international, and systemic levels for explaining states' emission patterns. For instance, democratic forms of government are mainly associated with a "greener" behavior, although the empirical evidence for a link between democracy and better environmental performance at the outcome level is mixed. States, which are also more embedded in the international system, may be more inclined to contribute to the global environmental good and, thus, have on average lower emission rates. Other prominent factors pertain to population, trade relationships, foreign direct investment, or civil society lobbying. Gassebner, Lamla and Sturm (2011) provide a recent meta analysis using Extreme Bounds Analysis and demonstrate that the strongest predictors of environmental quality and emissions pertain to the economic conditions of a country and, most prominently, GDP per capita. Although empirical evidence for the existence of an Environmental Kuznets Curve (EKC) (Selden and Song, 1994; Grossman and Krueger, 1995), i.e., countries' CO_2 emissions first increase with development, but then decline once a tipping point has been reached, is mixed (e.g., Aklin, 2016; Dasgupta et al., 2002; Itkonen, 2012), GDP per capita usually is robustly associated with emissions. The functional form may vary, though.

Ward, Greenhill and Bakke (2010) forcefully remind us that empirical results in the form of regression coefficients may not tell us much about how states' emission patterns will develop in the future. Policy prescriptions cannot be based on statistical summaries of probabilistic models. Moving from empirical analyses based on statistical significance to prediction offers a more solid scientific basis for assessing future levels of emissions, which is highly relevant both from a policy and scholastic perspective. And, in fact, a significant amount of studies have sought to actually predict CO_2 emissions for a global sample, in specific regions, or for individual countries for the future (e.g., Schmalensee, Stoker and Judson, 1998; Auffhammer and Carson, 2008; Van Vuuren and Riahi, 2008; Van Vuuren et al., 2011; Pao and Tsai, 2011; Auffhammer and Steinhauser, 2012; Durante et al., 2012; Kavoosi et al., 2012; Peters et al., 2013; Field et al., 2014; Zhao and Du, 2015; Pérez-Suárez and López-Menéndez, 2015; Le Quéré et al., 2016; Riahi et al., 2017). On one hand, there are those prediction and forecasting studies that are part of the IPCC Assessment Reports, i.e., the RCPs (since 2009) or their predecessor, the Special Report on Emission Scenarios (SRES; in 2000) (see Nakicenovic et al., 2000; Peters et al., 2013). On the other hand, the are prediction and forecasting studies "outside" the IPCC. In that context, one of the most prominent predictions of CO_2 emissions is given by Schmalensee, Stoker and Judson (1998) who use a reduced-form model to prediction emissions until 2050. These authors focus on the time period from 1950 to 2050 and their projections, which are basically based on a combination of only predicted data on population and GDP as well as country and year fixed effects (hence, reduced form), suggest that IPCC forecasts may systematically underestimate emission patterns. In fact, their projections highlight that a peak in emissions may not be reached by 2050.

Zhao and Du (2015) explicitly build upon the reduced-form approach in Schmalensee, Stoker and Judson (1998), particularly due to its attractive built-in assumption of "change-as-usual" instead of "business-as-usual." To this end, it is assumed that "future climate policy would continue to be strengthened at roughly the historical pace" (Zhao and Du, 2015, p.40). The authors also intend to improve upon earlier work by using more updated data and the post-1997 period for making their predictions. Their analysis, based on a sample of OECD countries, emphasizes that a peak in emission output may be reached by 2030, and a reduction of about 25 percent in emissions by 2050 could well be a likely scenario, although this forecast varies a lot depending on whether China is included in the sample or not. Pérez-Suárez and López-Menéndez (2015) comprehensively review earlier prediction studies and, empirically, concentrate on the forecasting power of the EKC. Unlike most other studies in the literature, these authors explicitly assess the accuracy of their prediction model and show thereby that their approach significantly reduces the error in forecasts for most countries in their sample. Unlike Zhao and Du (2015), however, Pérez-Suárez and López-Menéndez (2015) rely on a "business-as-usual" approach and predict emissions until 2020 only. While a systematic, global analysis is missing in their study, the results suggest that some countries are likely to lower emissions by 2020, but others will not. Finally, Le Quéré et al. (2016) provide an emission projection until 2016 (based on the estimated global carbon budget until 2015), which suggests a slight growth as compared to 2015; and Riahi et al. (2017) not only introduce the SSPs to the scientific community, but derive quantitative projections of CO_2 emissions until 2100 using integrated assessment models. Riahi et al. (2017, p.162) find that emissions are likely to increase in three out of the five SSPs (SSP2, SSP3, and SSP5) until 2100, albeit at different growth rates. For two of the SSPs (SSP1 and SSP4), Riahi et al. (2017, p.162) report a decrease in total emissions, although the peak of these curves may be well after 2030.

In light of this overview, it is apparent that results are generally mixed: depending on the underlying assumptions about key predictors, emissions may increase or decrease after a specific tipping point has been reached until 2100. Some of this ambiguity may be explained by certain model specifications, though. For example, Zhao and Du (2015) mainly focus on OECD countries only in the post-1997 period and predict that CO_2 emissions will decrease by 25 percent by 2050. Moreover, their scenario data are based on the SRES (Nakicenovic et al., 2000), which have been replaced by the RCPs and the SSPs by now (Riahi et al., 2017; O'Neill et al., 2017). Pérez-Suárez and López-Menéndez (2015) analyze a global sample of states and forecast that some countries may increase their emissions until 2020 only, but others may not. Finally, the RCPs that were also part of the last IPCC report, identified four future scenarios for how emissions will develop until 2100. In three out of these four scenarios, CO_2 emissions are likely to rise at least until 2080; and even then, an eventual decline may not occur. As indicated above, I seek to make three central contributions to this end, which improve upon earlier work: based on Riahi et al. (2017), I explicitly consider the SSPs; I present a forecast for a global sample until 2100; and I assess the prediction accuracy of the underlying model.

2.2 Data and Empirical Strategy

My predictions and forecasts are based on an OLS regression model that analyzes data on CO_2 emissions. All (previous, current, and potential) states, for which data are available and are identified in the list of independent states (Gleditsch and Ward, 1999), are units of analysis and they are observed once every year. Thus, the structure of my data is monadic and is defined by the "state-year." I use data from the US Carbon Dioxide Information Analysis Center (Oak Ridge National Laboratory) and Appalachian State University that provide information on carbon dioxide emissions (in thousand metric tons of C) at this monadic, state level as the dependent variable.[3] CO_2 emissions are defined as "those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring." Data are currently available for the period from 1960 to 2014, and this is also the period I focus on when assessing the in-sample and out-of-sample prediction power of my model. The final dependent variable is log-transformed.

Coming to the predictors of this outcome variable, I employ the SSPs (Kriegler et al., 2012; O'Neill et al., 2014; O'Neill et al., 2017; Riahi et al., 2017). In the words of Hegre et al. (2016, p.2):

> "*The SSPs were developed to evaluate the uncertainty in how impacts of climate change and the ability to mitigate adverse societal effects may evolve as a function of socioeconomic drivers. The scenarios are designed to span a range of alternative futures and are shaped by different assumptions about society, including economic development, education improvements, and population growth. Unlike earlier scenarios developed by the climate change research community – such as the Special Report on Emissions Scenarios – the SSPs are explicitly decoupled from the physical processes associated with climate change. Instead, each pathway is defined in terms of challenges to climate change mitigation and adaptation. High challenges to mitigation are here understood as involving high dependence on fossil fuel-based energy and low levels of international cooperation on global environmental issues. High adaptation challenges are characterized by low development growth rates, low investments in human capital, and increasing economic inequality (O'Neill et al., 2017).*"

Table 1: Overview of SSPs' Global Characteristics

	Mitigation Challenges	Adaptation Challenges	Economic Growth	Population Growth	Education Attainment
SSP1 (Sustainability)	Low	Low	High	Low	High
SSP2 ("Middle of the Road")	Medium	Medium	Medium	Medium	Medium
SSP3 (Fragmentation)	High	High	Low	High	Low
SSP4 (Inequality)	Low	Low	Medium	Medium	Low
SSP5 (Conventional Development)	High	Low	High	Low	High

Source: Hegre et al. (2016) and Chateau et al. (2012).

There are five different SSPs, which seek to capture different combinations of adaptation and mitigation scenarios (Table 1; for a more detailed overview, see Riahi et al. (2017) and O'Neill et al. (2017)), and are based on historical data and future projections of *inter alia* three key variables: population, GDP per capita, and the proportion of young males with upper secondary schooling or higher. Information on these variables is available until 2013. Hence, the values of the SSP variables are identical and differences

[3]Available at: `http://cdiac.ornl.gov/trends/emis/overview_2014.html`.

among these indicators – and therefore the different adaptation and mitigation scenarios based on the SSP predictors – only emerge in the post-2013 period.[4] In the following, I describe the variables, their theoretical rationale, and their operationalization in detail.

First, the SSPs use GDP per capita and secondary educational attainment to capture socioeconomic development. The GDP per capita data stem from the World Development Indicators[5] and are measured in constant 2005 USD. This variable is based on a country's gross domestic product divided by midyear population, and is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data beyond 2013 are based on "an augmented Solow growth model with representations of human capital and fossil fuel usage, known as the OECD ENV-Growth model (Chateau et al., 2012)" (Hegre et al., 2016, p.3). Second, education attainment focuses on men aged 20-24 and secondary schooling or higher. Historical data (since 1970) and projections are taken from the IIASA and Wittgenstein Center for Demography and Global Human Capital[6] model (Samir and Lutz, 2014; Lutz et al., 2007), while values in 1960-1969 stem from (Hegre et al., 2016) who extrapolated missing values assuming similar rates of change as for the period in which data are available. Related to this is, thirdly, population, which is also taken from the IIASA and the Wittgenstein Center for Demography and Global Human Capital model (Samir and Lutz, 2014; Lutz et al., 2007).

GDP per capita, or economic development, is one of the strongest predictors of carbon dioxide emissions (e.g., Pérez-Suárez and López-Menéndez, 2015; Zhao and Du, 2015). Moreover, all else being equal, a larger population is normally associated with a higher emission rate. And educational attainment not only captures human development, but should also proxy state capacity and technological sophistication (Jänicke, 1985, 2008; Bernauer and Böhmelt, 2013*b*). Due to the skewed distribution of population and GDP per capita, I employ log-transformed versions in my model. Finally, in light of the discussion on the EKC (Selden and Song, 1994; Grossman and Krueger, 1995), I also consider the squared term of *GDP per capita (ln)*.

Next to the substantive predictors pertaining to the SSPs, I also include country fixed effects and a year trend. The country fixed effects capture any time-invariant state-specific factors that may affect countries' emission patterns. These unit dummies are included for both the prediction accuracy tests as well as the forecast until 2100. The year trend is considered for both empirical approaches as well, while it addresses time dependencies more generally and technological advancement as a *systemic influence*:[7] higher values pertain to more technological sophistication (Jänicke, 1985, 2008; Bernauer and Böhmelt, 2013*b*). Year fixed effects address the same issue as the time trend, but the results presented below are qualitatively the same when replacing the year trend by year dummies.[8] Note that the year trend also

[4]As a result, I only estimate one model when examining the in-sample and out-of-sample prediction power as predictor values part of the SSP variables do not vary across the five SSP scenarios before 2014.

[5]Available at: `http://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

[6]Available at: `http://witt.null2.net/shiny/wic/`.

[7]This differs from education above as educational attainment focuses on the country level, not the system.

[8]Auffhammer and Carson (2008, p.237) recommend against using year fixed effects as "forecasting model selection criteria

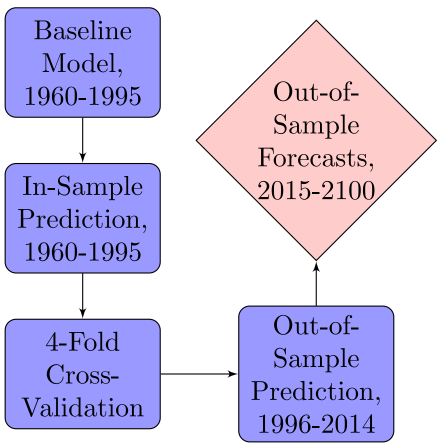
(partly) corrects for the potential non-stationarity of the variables involved: variables with a trend are likely to correlate as well, although this might be spurious. A year variable then addresses "co-trending" of items as it controls for the time trend common to all variables. In fact, as I demonstrate below, the time trend is statistically significant and, thus, seems to capture an effect that is not explained by the other variables in the model.[9]

The following equation summarizes the model I will be using for the predictions and forecasts, with $Y_{it}(ln)$ pertaining to the logged CO_2 emissions (dependent variable), X_{it} stands for the battery of covariates (i.e., logged income, its square term, logged population, and education), Z_{it} refers to the country fixed effects, and $Year_t(ln)$ pertains to the year-trend variable (also logged).

$$Y_{it}(ln) = \alpha + \beta * X_{it} + \gamma * Z_{it} + \pi * Year_t(ln)$$

With this data setup, to arrive at the forecast of emission patterns in 2015-2100, I complete the following steps. First, for determining the prediction accuracy of this model, I estimate it on a time-series cross-sectional sample for the period from 1960 to 1995, which I then assess with in-sample techniques. I have chosen 1995 as the cut-off point as the "strengthening of global climate policy may have been accelerated" (Zhao and Du, 2015, p.40) around that time. Second, I also examine the out-of-sample prediction power by employing a 4-fold cross-validation exercise and comparing my predictions for 1996 to 2014 (based on the estimates for the 1960–1995 period) with actually observed values (for which I have data). The final forecast for the 2015-2100 period is based on a model that uses data in 1960-2014 and I present results for the different SSP scenarios. Figure 1 summarizes these steps for illustrative purposes.

Figure 1: Combination of Statistical Model, Prediction Accuracy Tests, and Forecast



punish [this] quite heavily." Instead, they suggest using a time trend variable, which is my approach.

[9] I return to this issue in the Supplementary Materials.

3 In-Sample Prediction

I begin by assessing how effective the model actually is in predicting emission patterns *in-sample*. Put differently, how accurate are the "conditional statements about a phenomenon for which the researcher actually has data, i.e., the outcome variable has been observed?" (Bechtel and Leuffen, 2010, p.311). To assess this, I first estimate the baseline model in 1960-1995 with OLS, then calculate the predicted values of this model for that period in time, and compare the predicted yearly median levels of CO_2 emissions using the estimated parameters from the baseline model with the truly observed median emission rate between 1960 and 1995.

Table 2: Baseline Model for CO_2 Emissions (ln) – 1960-1995

	Model 1
GDP per capita (ln)	1.069***
	(0.126)
GDP per capita^2 (ln)	−0.021***
	(0.008)
Population (ln)	1.286***
	(0.039)
Education	0.021
	(0.131)
Year Trend	0.096***
	(0.013)
Constant	−11.275***
	(0.583)
Observations	4.733
Prob > F	0.000
Adjusted R^2	0.979

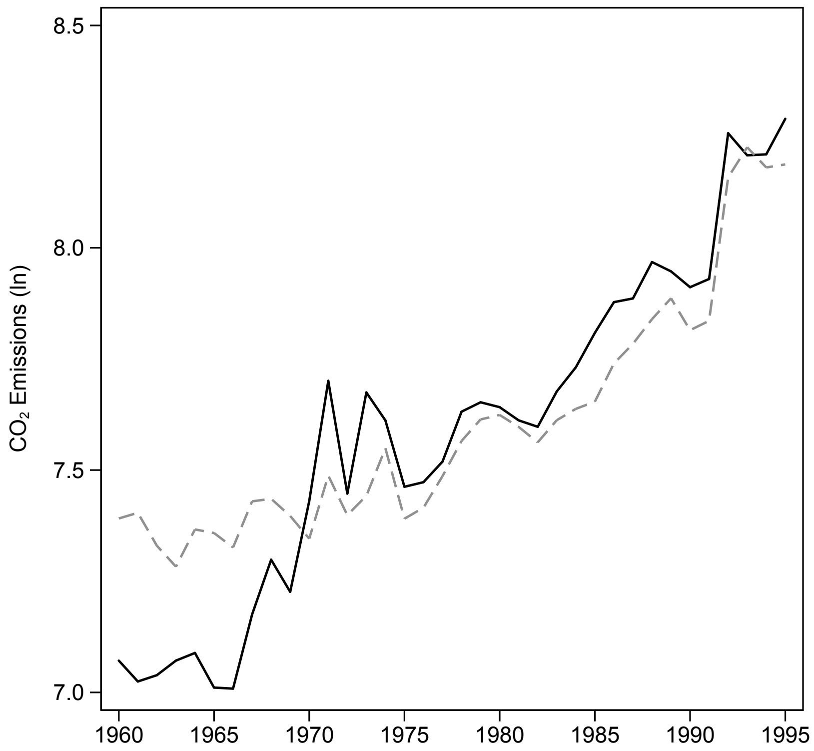
$*p < 0.10, **p < 0.05, ***p < 0.01$

Standard errors in parentheses. Country fixed effects included, but omitted from presentation.

Table 2 summarizes the underlying model's results. Most variables "behave" as expected and are statistically significant. *Education* is the only exception as it does not reach a conventional level of significance. Using this model, I then calculated predicted values to compare the predicted median year value (of all countries) of CO_2 emissions with the yearly median value based on actually observed data. The results are depicted in Figure 2: while the dashed grey line captures the predicted values as derived from the parameters of the model (Table 2), the solid black line pertains to the actually observed values. The figure shows that the model is able to capture CO_2 emissions relatively accurately, although some deviations from actually observed values do exist. For example, emissions are overpredicted until the early 1970s, but afterwards slightly underpredicted. Having said that, this figure demonstrates that the predicted values fit the time points of the actually observed data reasonably well.

To assess the accuracy of this prediction more thoroughly, I follow Pao and Tsai (2011, p.2454) and use three goodness-of-fit measures: the mean squared prediction error (MSPE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) (see Chatfield, 1996, 2000). The MSPE pertains to the expected value of the squared difference between the actually observed values of CO_2

Figure 2: Median Levels of CO_2 Emissions (ln) – 1960-1995



Note: Dashed line pertains to predicted values. Solid line pertains to actual values.

emissions and the predicted values. The MAE is the expected value of the absolute difference between the actually observed values of CO_2 emissions and the predicted values. Finally, the MAPE is defined by the average of the unsigned percentage error, i.e., it is the expected value of the absolute difference between the actually observed values of CO_2 emissions and the predicted values divided by the actually observed values. All these statistics are relatively easy to compute and interpret: the closer any of these statistics is to 0, the more accurate is the model in making predictions. However, the MSPE and the MAE are scale-dependent; only the MAPE is not. Pao and Tsai (2011) and Lewis (1982) suggest to this end focusing mainly on the MAPE, where less than 10 percent of error constitute a highly accurate forecast, 10-20 percent stand for a good one, and 20-50 percent may still be seen as a reasonable forecast. More than 50 percent of error according to the MAPE are seen as inaccurate.

The MSPE value of the prediction exercise underlying Figure 2 is 0.129, the MAE is 0.240, and the MAPE is 0.041. Correspondingly, these formal test statistics also suggest that the in-sample power of my model is given in 1960-1995. For example, the absolute percent error according to the MAPE is only 4.1 percent, i.e., the prediction is "off" by only about 4 percent. It remains to be seen, though, how accurately this model predicts emissions when moving to the "harder" test of an *out-of-sample* prediction and the model is confronted with "new" data.

4 Out-of-Sample Prediction

Hypothesis testing that ignores out-of-sample heuristics faces the inherent risk of fitting to a specific sample's idiosyncrasies, rather than identifying stable structural relationships between a dependent variable of interest and its determinants (see Ward, Greenhill and Bakke, 2010). In fact, if a model explains the relationship between, in my case, emission behavior and the SSP variables fairly well in-sample, we merely assume that it also performs well when presented with new data (i.e., out-of-sample). Yet, if the model only gives a description of this relationship in the original data set without capturing underlying causal relations, then making correct and useful predictions with new data is likely to be undermined (see Beck, King and Zeng, 2000; Ward, Greenhill and Bakke, 2010).

For the out-of-sample analyses, I begin with a 4-fold cross-validation quasi-experimental exercise, which I repeated 10 times for the baseline model (Model 1 above, 1960-1995). For this cross-validation, I randomly divide the sample underlying Model 1 into four segments of about the same size. I then use three random segments to estimate the parameters, while the fourth segment, also called the "test set" (Ward, Greenhill and Bakke, 2010, p.370), is retained for assessing the predictive power of the baseline model on the pooled subsets. Therefore, I use three segments of the data to build the model and create predictions, while a last (randomly chosen) part of the data is not considered for estimating the model in the first place, but I merely use it for comparing predicted with observed values, i.e., assessing the predictive power of the model. As in the in-sample analysis above, I rely on the MSPE, the MAE, and the MAPE. I repeat this procedure 10 times and also calculated the average values of the prediction accuracy measures across these 10 exercises. Eventually, the purpose of this approach is to assess the model's predictive power when trying to correctly predict emissions that are not "within the very same set of data that was used to generate the models in the first place" (Ward, Greenhill and Bakke, 2010, p.8). See Ward, Greenhill and Bakke (2010, p.370), for example, for a more detailed discussion of this approach. Table 3 summarizes the findings.

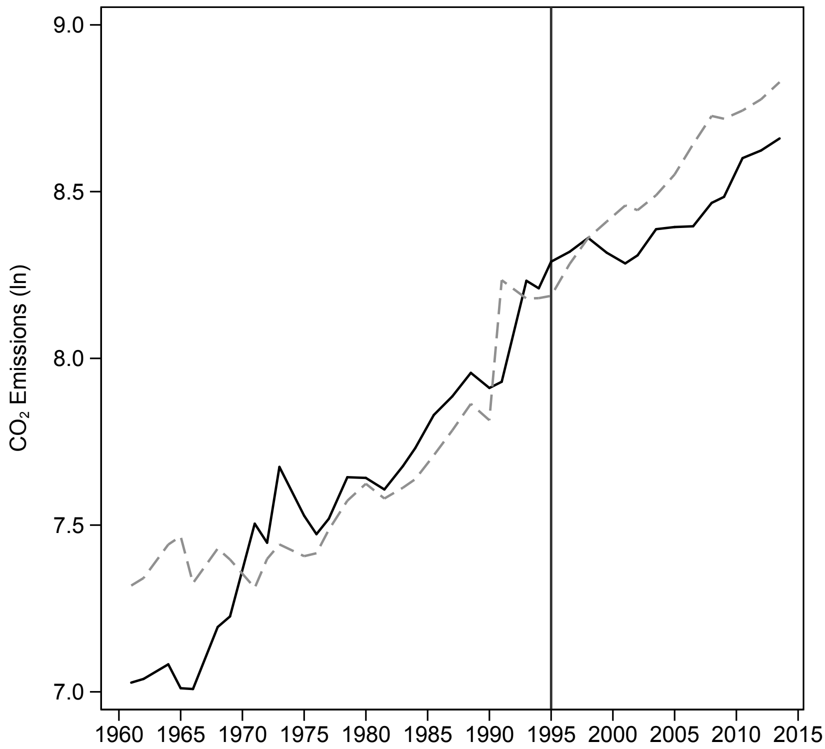
Table 3: 4-Fold Cross-Validation Exercise – Summary

Cycle Run	MSPE	MAE	MAPE
1	0.138	0.249	0.043
2	0.142	0.250	0.043
3	0.140	0.250	0.043
4	0.137	0.249	0.042
5	0.142	0.251	0.043
6	0.142	0.251	0.043
7	0.140	0.249	0.042
8	0.139	0.249	0.043
9	0.140	0.250	0.043
10	0.140	0.250	0.043
Mean Value	0.140	0.250	0.043

Not surprisingly, the prediction power of the model decreases when confronted with new data in this

4-fold cross-validation, although it remains at reasonably high levels. The MSPE increases from 0.129 in the in-sample prediction to 0.140 in the validation exercise. Similarly, the MAE is raised from 0.240 to 0.250, while the MAPE changes from 0.041 to 0.043.

Figure 3: Median Levels of CO_2 Emissions (ln) – 1960-2014



Note: Dashed line pertains to predicted values. Solid line pertains to actual values. Vertical solid line marks end of in-sample prediction period (1995).

In a second step to assess the out-of-sample prediction power of the model, similar to Figure 2 above, I also graphically depict predicted and actual values of yearly median emission rates. The difference between Figure 2 and Figure 3 is, however, that the latter extends the period of study and, hence, the predictions to 2014, although the period from 1996 to 2014 is not used for building the model. We can then compare the actually observed values with predicted ones (1) in 1960-1995 that is my "observed" period of time that I also use for constructing the model (Table 2 above) and (2) in 1996-2014 that is the period of time that I have not used for building the model and I treat as "unobserved" although I know the true values. Figure 3 depicts the results. On one hand, actual and predicted values are very similar and seem to follow the same trend. On the other hand, there does not seem to be a systematic bias in the predictions for 1996-2014, i.e., the period I did not consider for the model estimation. The predicted values first seem to slightly underpredict actual emission rates by a bit, before they are slightly higher than what has actually been observed. The corresponding values for the MSPE, MAE, and MAPE are 0.178, 0.301, and 0.045. That is, the prediction accuracy is slightly worse than in the case of the cross-validation.

Two main conclusions can be derived from these two out-of-sample analyses. First, uncertainty remains and the predictions for the "unobserved" data partition are less accurate than in the in-sample case. This is demonstrated by the goodness-of-fit measures, which all increase and therefore show that prediction power decreases; and by the comparison of observed and predicted values for the period from 1996 to 2014 in Figure 3, where I use an existing model (that is based on 1960-1995) to predict an outcome with "new" data, i.e., data that have not been used to construct the model originally (in 1996-2014). Second, having said that, prediction accuracy is reasonably strong, even when confronting the model with new data. The goodness-of-fit statistics and Figure 3 emphasize this. For instance, the absolute percent error according to the MAPE never approaches 5.0 percent. Hence, I now come to the core contribution of this article: the out-of-sample forecast of CO_2 emissions in 2015-2100.

5 Out-of-Sample Forecast until 2100

I begin by summarizing the underlying model that I use for the forecast. This model is fully based on the first model in Table 2 with one exception: I no longer restrict the time period used for building the model's parameters to 1960-1995, but use the entire time period for which data of my dependent variable do exist, i.e., 1960-2014. Table 4 summarizes my results: the estimates are virtually identical to Table 2 above. There is evidence of an inverted U-shaped relationship between GDP per capita and CO_2 emissions, larger populations are associated with more emissions, and *Education* is now statistically significant at the 1 percent level. However, and after having positively assessed the prediction power of this model in-sample and out-of-sample, the key question is how this model predicts emissions for the time period from 2015 to 2100.

Table 4: Baseline Model for CO_2 Emissions (ln) – 1960-2014

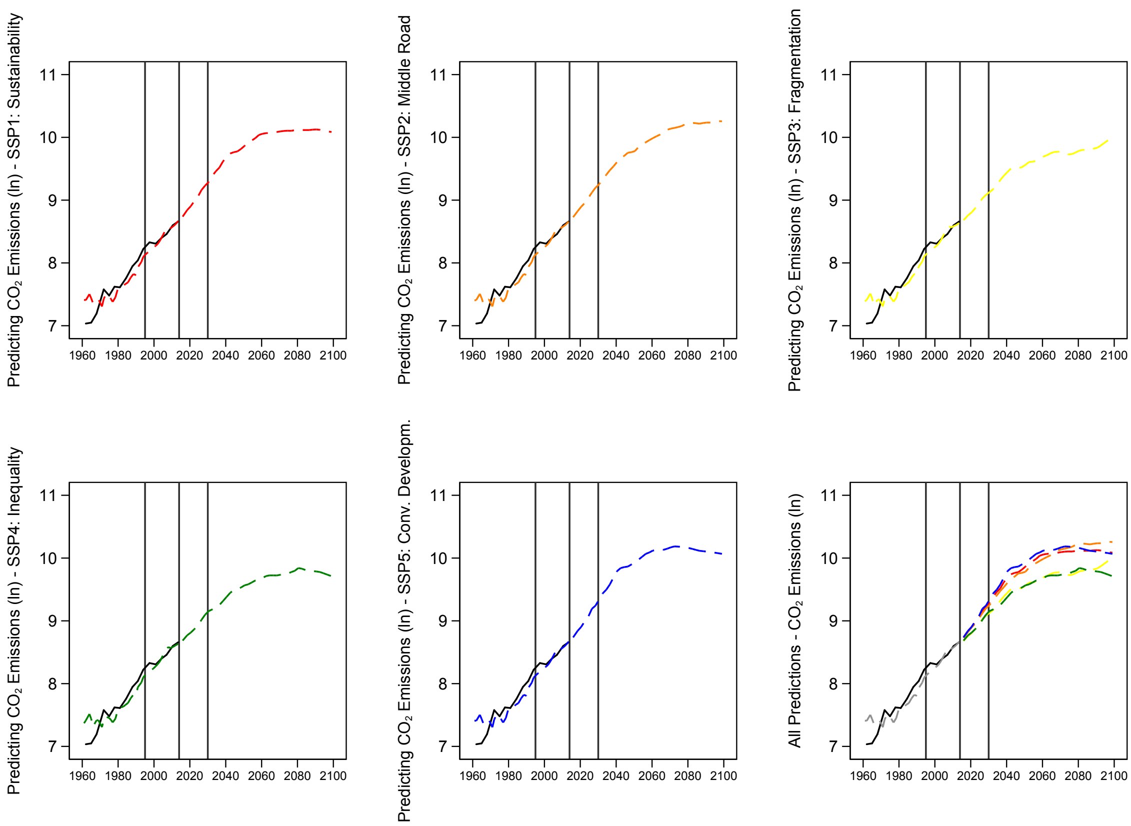
	Model 2
GDP per capita (ln)	2.078***
	(0.078)
GDP per capita^2 (ln)	−0.086***
	(0.005)
Population (ln)	1.189***
	(0.021)
Education	0.595***
	(0.073)
Year Trend	0.057***
	(0.010)
Constant	−13.804***
	(0.357)
Observations	7.795
Prob > F	0.000
Adjusted R^2	0.978

$*p < 0.10, **p < 0.05, ***p < 0.01$

Standard errors in parentheses. Country fixed effects included, but omitted from presentation.

To this end, I calculated the predicted values for CO_2 emissions in 1960-2100, based on Model 2 (Table 4) that focuses on 1960-2014, for the five different SSPs. Each SSP is associated with its own combination of GDP per capita, population, and education values (see Table 1), and projections of these variables until 2100. Hence, I re-estimated Model 2 five times, each time using a different combination of variable values pertaining to a specific SSP. After each of the five model estimations, I calculated the predicted values for CO_2 emissions in 1960-2100. This constitutes the true forecast then. Recall that all SSP scenario values for GDP per capita, population, and education are the same before 2014. I plot the predicted values of each SSP forecast next to the observed values that are given for the 1960-2014 period. I also compare and contrast the SSPs in the last panel of Figure 4 with each other directly.

Figure 4: Median Levels of CO_2 Emissions (ln) – 1960-2100



Note: Dashed lines pertain to predicted values according to different SSP scenarios. Solid line pertains to actual values. Vertical solid lines mark end of in-sample prediction period (1995), end of period in which CO_2 emission data are available (2014), and the IPCC turning point (2030).

Figure 4 points toward several important conclusions. First, the forecasts suggest that emissions will increase over time, regardless of which scenario we look at (the forecasts are also not statistically different from each other). Second, *none* of the five SSPs is associated with a peak in emissions reached by 2030. According to all scenarios, emissions are likely to rise well after 2030. Third, it seems, however, that a peak might be reached between 2060 (e.g., SSP1) and 2080 (e.g., SSP4), although this does not imply that emissions will fall (shortly) afterwards. In fact, only SSP4 and SSP5 are associated with a decreasing slope of the median emission level when approaching 2100. The other scenarios seem to remain relatively stable once the maximum has been reached. Fifth, the average yearly median level of emissions across all five scenarios is 22,841.40 Kt (0.023 Gt) per country in 2100. This corresponds to 4.44 Gt (based on N=193 for 2014, taking current United Nations membership as a reference point), which pertains roughly to a scenario between RCP4.5 and RCP3-PD (Peters et al., 2013; Jordan et al., 2013, p.753). The RCP4.5 scenario is generally linked to a global average temperature increase between 2 and 3 °C, while RCP3-PD is associated with an average temperature rise between 1.3 and 1.9 °C.

My findings, as they are based on the SSPs that do incorporate mitigation and adaptation strategies, point to lower total emissions than "most non-climate policy scenarios," which "predict emissions of the order of 15 to 20 Gt by the end of the century" (Van Vuuren et al., 2011, p.20). In sum, although my forecast suggests a "more optimistic" future than any projection in Riahi et al. (2017, p.162), where total global emissions in 2100 range between 25 Gt and 120 Gt of CO_2 emissions, and than RCP8.5 (4-6.1 °C) or RCP6 (2.6-3.7 °C) (Peters et al., 2013; Jordan et al., 2013, p.753), it highlights that circumstances are likely to be worse than in the case of RCP3-PD (1.3-1.9 °C). The predictions are also generally in line with what Le Quéré et al. (2016, p.626, Figure 4) present for 2016. But it is interesting to see that none of my findings, in fact, is compatible with reaching a peak in emissions by 2030, significantly reducing emissions afterwards (or at any point in the future), and thus achieving the 2 °C goal (e.g., Jordan et al., 2013; Field et al., 2014) as such. Ultimately, the results, considering them in their entirety, suggest that meeting the 2 °C goal, i.e., the world community seeking to limit global average temperature rise to within 2 °C (e.g., Field et al., 2014), may not be achieved. This assessment is in line with Jordan et al. (2013, p.752), among others, who also consider the possibility that the goal might be "pushed out of reach altogether."

6 Conclusion

Assessing the predictive power of empirical models and forecasting state behavior in the future have important implications for scholars and can also offer significant benefits for policymakers. With this research, I sought to build upon and extend earlier work on predicting CO_2 emissions by employing the shared socioeconomic pathways (SSPs) (Kriegler et al., 2012; O'Neill et al., 2014; O'Neill et al., 2017; Hegre et al., 2016; Riahi et al., 2017) as predictors. This article has sought to make three central contributions to the literature. First, as one of the first studies (for an exception, see Riahi et al., 2017), I have improved upon the RCPs by incorporating the SSPs. Second, I forecasted for a global sample in 1960-2100, which circumvents issues of limited time periods and sample selection bias in previous research. Third, I assessed the prediction accuracy of the model.

The results of my research suggest that none of the SSP scenarios is likely to be associated with an emission output that may be compatible with reaching the 2 °C goal (e.g., Jordan et al., 2013; Field et al., 2014) in light of anticipated adaptation and mitigation policies. While these are directly incorporated into the SSPs, recall as well that the reduced-form model I have employed also assumes "change-as-usual" (Zhao and Du, 2015; Schmalensee, Stoker and Judson, 1998). However, my research strongly emphasizes that more efforts are necessary than currently in place or even anticipated by my model. In a recent article, Jordan et al. (2013) discuss various policy alternatives *if* the 2 °C goal may not be met for preventing further risks and damage. My work highlights that studying these alternatives again, linking them to current predictions and climate models, and seeking to implement them in the most cost-efficient and effective way seems indeed paramount. Note, however, that after assessing potential costs and comparing them with likely benefits, Jordan et al. (2013) conclude that recommitting to the 2 °C goal may actually the best alternative.

It is worth noting that the my forecasts are based on some fairly restrictive assumptions (see also Hegre et al., 2013): that the forecasts for my predictors turn out to be correct, that the past relationship between the predictors and emissions will continue to hold in the future, and that my model captures all major factors. All of these premises can be questioned. I conclude, nevertheless, that my results are substantively important and point to crucial implications for scholars and policymakers alike.

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