Volume 47, Number 1, March 2022

ARFIMA REFERENCE FORECASTS FOR WORLDWIDE CO2 EMISSIONS AND THE NATIONAL DIMENSION OF THE POLICY EFFORTS TO MEET IPCC TARGETS [*]

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We use an ARFIMA approach to develop reference scenario projections for CO2 emissions worldwide and for seven different regions. Our objective is to determine the magnitude of the policy efforts necessary to achieve the IPCC emissions reductions goals. For worldwide emissions, the aggregate policy effort required to achieve the 2050 goals is equivalent to 97.4% of 2010 emissions. This policy effort is frontloaded as about 60% of such efforts would have to occur by 2030. In order to achieve the IPCC target the policy efforts in the cases of the USA, EU(28), Russia, and Japan are lower and less frontloaded than the IPCC goals themselves. In the case of China, India and the ROW, additional policy efforts are necessary to achieve reductions in emissions of 105.0%, 156.0% and 111.4%, of the 2010 levels, respectively. In the case of India, policy efforts are not only rather severe but also rather dramatically frontloaded, as about 74% of the policy efforts would have to occur by 2030.

Keywords: CO2 Emissions, IPCC Emission Targets, Long Memory, ARFIMA
JEL Classification: C22, C53, O52, Q54

1. INTRODUCTION

The purpose of this article is to provide reference forecasts for aggregate CO2

[*] This is one of two twin papers on the issue of developing new reference CO2 emissions forecasts and identifying their implications for the policy efforts towards decarbonization. The other paper "ARFIMA Reference Forecasts for Worldwide CO2 Emissions and the Need for Large and Frontloaded Decarbonization Policies" focuses on aggregate worldwide CO2 emissions by source – solid fossil fuels, liquid fossil fuels, natural gas, cement production, and gas flaring. The first author would like to acknowledge financial support from FCT–Fundação para a Ciência e a Tecnologia (grant UID/ECO/04007/2019).

emissions for the six largest regional emitters – China, the USA, the European Union, India, Russian, and Japan, as well as the Rest of the World (ROW, henceforward), based on an ARFIMA approach. Our ultimate objective is to compare our reference forecasts with the relevant policy emissions targets set up by the IPCC and thereby ascertain the magnitude of the policy effort necessary across different regions of the world to achieve such targets.

There is strong scientific evidence confirming the warming the planet's climate system, with increasing temperature of the atmosphere and oceans, rising sea levels, melting ice, among others, whose most likely causes are the increased concentration of anthropogenic greenhouse gas emissions in the atmosphere (IPCC, 2014).

Recently, the IPCC (2018) report has pointed that limiting global warming to 1.5°C would require "rapid and far-reaching" transitions in land, energy, industry, buildings, transport, and cities. Global net anthropogenic emissions of CO2 would need to fall by about 45% from 2010 levels by 2030, reaching carbon neutrality by 2050. The IPCC suggests that the natural carbon sequestration capacity by 2050 will be approximately 15% of the 2010 reference emissions. Accordingly, carbon neutrality requires by 2050 a reduction of 85% of 2010 emission levels. The question remains, however, as to the magnitude and timing of the policy efforts necessary to achieve such goals.

Identifying the proper reference scenario is critical first step in ascertaining the extent of the policy effort required to achieve any policy target for CO2 emissions. Specifying a reference scenario in the typical "business as usual" projections, means predicting a path to CO2 emissions that reflect existing demographic trends, prospective trends for energy and industrial processes, for the services, residential, transport and waste sectors, as well as, ongoing policy commitments. This conventional approach to establishing reference scenarios, however, introduces a large number of working assumptions and a great degree of arbitrariness in their specifications, thereby clouding the information it intends to provide.

This paper uses an ARFIMA approach to provide reference forecasts for worldwide CO2 emissions based on a comprehensive univariate statistical analysis of the different time series and recognizing the possible presence of long-memory through fractional integration. Accordingly, our forecasts are based strictly on the most basic statistical fundamentals of the stochastic processes that underlie CO2 emissions. As such, they capture the information included in the sample, and implicitly assume that the observed trends will continue in the future. Thus, these forecasts provide the most fundamental reference case forecast of CO2 emissions (Belbute and Pereira, 2015, 2017).

There is now an extensive literature on fractional integration, which goes beyond the stationary/non-stationary dichotomy to consider the possibility that variables may follow a long memory process (see, among others, Diebold and Rudebusch (1991), Lo (1991), Sowell (1992a) and Palma (2007)). The ARFIMA methodology is inspired by a budding literature on the analysis of energy and carbon emissions based on a fractional integration approach (see, for example, Barassi et al. (2011), Apergis and Tsoumas, (2011, 2012), Barros et al. (2016), Gil-Alana et al. (2015) and Belbute and Pereira

(2015, 2017)).

Measuring the persistence of CO2 emissions is of utmost importance for the design of energy and environmental policies. If emissions are stationary, then transitory public policies will tend to have only transitory effects. Permanent changes, therefore, require a permanent policy stance. On the other hand, if emissions are not stationary, then even transitory policies will have permanent effects on emissions, and a steady policy stance is less critical (see, for example, Zerbo and Darné (2019)).

The fractional integration approach goes beyond this dichotomy to consider the possibility that variables may follow a long-memory process. This long-range dependence is characterized by a hyperbolically-decaying autocovariance function, and by a spectral density that approaches infinity as the frequency tends to zero. Long memory, therefore, implies a significant dependence between observations widely separated in time, and, as such, the effects of policy shocks may be temporary but long lasting. Accordingly, this property has important policy implications for the specification of long-term reference case scenarios for CO2 emissions.

Finally, our methodological framework has to be understood also in the context of the current debate on which benchmark should be used to assess policy efforts and monitor the achievement of the goals associated, for example, with the UN Sustainable Development Goals or different decarbonisation goals. Indeed, our ARFIMA projections reflect the CO2 emissions that should exist at a future date in the absence of the target rather than the value recorded in a particular year, as was the case with the Kyoto Protocol targets and, more recently, with the Paris agreement (Markandaya et al., 2019).

The remainder of this paper is organized as follows. Section 2 presents and describes the data set. Section 3 provides a brief technical description of the methodology used. Section 4 discusses the empirical findings, considering first the fractional integration analysis and then the accuracy of in-sample forecasts. Section 5 presents and discusses our reference forecasts vis-à-vis the IPCC new targets. Finally, section 6 provides a summary of the results, and discusses their policy implications.

2. DATA: SOURCES AND DESCRIPTION

2.1. Data Sources

In this paper, we use annual data for global CO2 emissions for the period between 1950 and 2017. The data until 2014 is from the Carbon-Dioxide Information Analysis Centre (Boden et al., 2017). This data set contains information going back to 1870. Nevertheless, we have elected to work only with data starting in 1950, given the profound structural changes that occurred after World War II. Data for 2015-2017 is based on both the national emissions inventories collected by the United Nations (UNFCCC, 2018).

Aggregate CO2 emissions are the sum of five components: emissions from burning fossil fuels – solid/coal, liquid/oil, gas and gas flaring, and emissions from cement production. It does not consider emissions from land use, or land-use change and forestry. In terms of its regional decomposition we consider seven blocks: China; the USA; the EU(28), the 28 countries currently making up the European Union; India; the Russian Federation, including before 1991 the part of the USSR corresponding to Russia; Japan; and ROW. All variables are measured in million metric tonnes of carbon per year (Mt, hereafter), and were converted into units of carbon dioxide by multiplying the original data by 3.664, the ratio of the two atomic weights. entrepreneurial risk and provides some kind of insurance (Thornton and Flynn, 2003; Smith, 2018). It also reduces transaction costs between actors, search and information costs, bargaining costs, and decision costs (Landry et al., 2002).

2.2. Description of the Data

Table 1 presents summary information about our data. During the sample period, worldwide CO2 emissions grew incessantly, reaching its highest value of 36,767 Mt in 2017. This value is 65% above the emissions observed in 1990 and 10% above the 2010 levels.

CO2 emissions in China have steadily increased from 78Mt in 1950 to 9,839Mt in 2017, making it the world leader in emissions. China is currently responsible for 26.8% of worldwide emissions, a share that sharply increased over the sample period. In turn, CO2 emissions in the USA increased from 2,536Mt in 1950 to a peak of 6,132 Mt in 2005 and declined thereafter. In 2017, the USA contributed 5,270Mt to global emissions. This figure corresponds to 14.3% of worldwide emissions, making the USA the second largest polluter. This share, however, has been steadily decreasing since the 1950s when it reached 36.6%.

The EU(28) was responsible in 2017 for 9.6% of worldwide CO2 emissions making it the third largest polluting block. In 1950, this share was 30.1% and has consistently decreased ever since. EU(28) emissions peaked in 1979 at 4,724Mt and have declined particularly after 2005. On the other hand, in India, CO2 emissions have grown steadily from 66.7Mt in 1950 to 2,467Mt in 2017. India's emissions accounted for 1.1% of worldwide emissions in the 1950s. This share reached 6.7% in 2017, making India the fourth largest emitter.

Russia is the fifth largest CO2 emitter having contributed in 2017 about 4.6% of worldwide emissions. Emissions increased from 418Mt in 1950 to 1.693 in 2017, with a peak of 2.571Mt in 1990. Russia’s sharp drop in emissions in the 1990s is due to the breakup of the USSR in 1991. In turn, in Japan, CO2 emissions reached 1,205Mt in 2017, which represents 3.3% of worldwide emissions and makes Japan the sixth largest regional CO2 emitter. Finally, CO2 emissions from the ROW have increased persistently over the sample period, from 972Mt in 1950 to 12,751Mt in 2017. The share of emissions from the ROW in worldwide emissions increased from 18.6% in the 1950s to 34.7% in 2017.

Table 1. CO2 Emissions from Fossil Fuel Combustion and Cement Production

Years	Global Mt	China	USA	EU(28)	India	Russia	Japan	ROW
	Average Shares of Total Worldwide CO2 Emissions (%)							
1950-1959	7391	3.2	36.6	30.2	1.1	8.3	2.0	18.6
1960-1969	11292	4.6	29.8	28.3	1.4	10.0	3.5	22.4
1970-1979	17141	6.4	27.0	25.2	1.4	10.4	5.1	24.4
1980-1989	20003	9.4	22.9	21.9	2.1	11.5	4.7	27.6
1990-1999	23077	13.0	23.6	18.5	3.5	8.0	5.2	28.2
2000-2009	28613	18.6	21.1	14.9	4.3	5.6	4.4	31.0
2010-2017	35592	26.8	15.4	10.3	5.9	4.7	3.5	33.4
2010	33445	25.4	17.0	11.8	5.1	5.0	3.6	32.1
2017	36767	26.8	14.3	9.6	6.7	4.6	3.3	34.7

3. FRACTIONAL INTEGRATION

3.1. Fractionally Integrated Processes

A fractionally-integrated process is a stochastic process with a degree of integration that is a fractional number, and whose autocorrelations decay slowly at a hyperbolic rate of decay. Accordingly, fractionally-integrated processes display long-run rather than short-term dependence and for that reason are also known as long-memory processes.

A time series $x_t = y_t - \beta z_t$ is said to be fractionally integrated of order d, if it can be represented by

$$(1-L)^d x_t = u_t, \quad t = 1, 2, 3, \cdots, n, \tag{1}$$

where, β is the coefficients vector, z_t represents all deterministic factors of the process, y_t, and $t = 1, 2, 3, \cdots, n$, L is the lag operator, d is a real number that captures the long-run effect, and u_t is $I(0)$.

Allowing for values of "d" in the interval between 0 and 1 gives extra flexibility when modeling long-term dependence. Indeed, in contrast to an $I(0)$ time series (where $d = 0$) in which shocks die out at an exponential rate, or an $I(1)$ process (where $d = 1$) in which there is no mean reversion, shocks to the conditional mean of an $I(d)$ time series with $0 < d < 1$ dissipate at a slow hyperbolic rate. More specifically, if $-0.5 < d < 0$, the autocorrelation function decays at a slower hyperbolic rate but the process has a rebounding behavior or a negative correlation. If $0 < d < 0.5$, the process reverts to its mean but the auto-covariance function decreases slowly as a result of the strong dependence on past values. The effects will last longer than in the pure stationary case ($d = 0$). If $0.5 < d < 1$, the process is non-stationary with a time-dependent variance, but the series retains its mean-reverting property. Finally, if $d \geq 1$, the process is non-stationary and non-mean-reverting, i.e. the effects of random shocks are permanent (for details see, for example, Granger and Joyeux (1980), Granger (1980, 1981), Sowell (1992a, 1992b), Baillie (1996), Palma (2007) and Hassler et al. (2016), Belbute and Pereira (2015)).

3.2. ARFIMA Processes

An ARFIMA model is a generalization of the ARIMA model which frees it from the I(0)/I(1) dichotomy, therefore allowing for the estimation of the degree of integration of the data generating process. In an ARMA process the AR coefficients alone are important to assess whether or not the series is stationary. In the case of the ARFIMA model, the $AR(p)$ and $MA(q)$ terms are treated as part of the model selection criteria. Accordingly, the ARFIMA approach provides a more comprehensive and yet more parsimonious parameterization of long-memory processes than the ARMA models.

Moreover, in the ARFIMA class of models, the short-run and the long-run dynamics is disentangled by modeling the short-run behavior through the conventional ARMA polynomial, while the long run is captures by the fractional differencing parameter, d (see, among others, Bollerslev and Mikkelsen (1996)).

If the process $\{u_t\}$ in (1) is an $ARIMA(p, q)$, then the process $\{x_t\}$ is an $ARFIMA(p, d, q)$ process and can be written as

$$\phi(L)(1 - L)^d x_t = \theta(L) e_t, \tag{2}$$

where

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ \ldots\ - \phi_p L^p = 0,$$
$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ \ldots\ + \theta_p L^q = 0$$

are the polynomials of order p and q respectivelly, with all zeroes of lying outside the unit circle, and with e_t as white noise. Clearly, the process is stationary and invertible for $-0.5 < d < 0.5$.

The estimation of the parameters of the ARFIMA model $\phi,\ \theta,\ d,\ \beta$ and σ^2 is done by the method of maximum likelihood. The log-Gaussian likelihood of y given parameter estimates $\hat{\eta} = (\hat{\phi}, \hat{\theta}, \hat{d}, \hat{\beta}, \hat{\sigma}^2)$ was established by Sowell (1992b) as

$$\ell\big((y|\hat{\eta})\big) = -\tfrac{1}{2}\{\boldsymbol{T}\log(2\pi) + \log|\widehat{\boldsymbol{V}}| + \boldsymbol{X}'\widehat{\boldsymbol{V}}^{-1}\boldsymbol{X}\}, \tag{3}$$

where X represents a $\boldsymbol{T}$- dimensional vector of the observations on the process $x_t = y_t - \beta z_t$ and the covariance matrix $\boldsymbol{V}$ has a Toeplitz structure.

3.3. ARFIMA Forecasting and Prediction-Accuracy Assessment

Given the symmetry properties of the covariance matrix, $\boldsymbol{V}$ can be factored as $\boldsymbol{V} = \boldsymbol{LDL'}$, where $\boldsymbol{D} = \mathrm{Diag}(v_t)$ and $\boldsymbol{L}$ is lower triangular, so that;

$$\boldsymbol{L'} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ \tau_{1,1} & 1 & 0 & \dots & 0 \\ \tau_{2,2} & \tau_{2,1} & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tau_{(T-1),(T-1)} & \gamma_{(T-1),(T-2)} & \tau_{(T-1),(T-3)} & \cdots & 1 \end{bmatrix}. \tag{4}$$

Moreover, let $\tau_t = V_t^{-1}\gamma_t$, $\gamma_t = (\gamma_1,\ \gamma_2, \dots,\ \gamma_t)'$ and V_t is the $t \times t$ upper left sub-matrix of $\boldsymbol{V}$.

Let $f_t = y_t - \beta z_t$. The best linear forecast of x_{t+1} based on $x, x_2, \dots\ x_t$ is

$$\hat{f}_{t+1} = \sum_{k=1}^{t} \tau_{t,k} f_{t-k+1}. \tag{5}$$

Moreover, the best linear predictor of the innovations is $\hat{\varepsilon} = L^{-1}f$, and the one-step-ahead forecasts for $\hat{y}$, in matrix notation, is

$$\hat{y} = \hat{L}^{-1}\big(y - Z\hat{\beta}\big) + Z\hat{\beta}. \tag{6}$$

Forecasting is carried out as suggested by Beran (1994) so that $\hat{f}_{T+k} = \tilde{\gamma}_k'\hat{V}^{-1}\hat{f}$, where $\tilde{\gamma}_k = (\hat{\gamma}_{T+k-1}, \hat{\gamma}_{T+k-2}, \dots, \hat{\gamma}_k)$. The accuracy of predictions is based on the average squared forecast error, which is computed as $MSE\big(\hat{f}_{T+k}\big) = \hat{\gamma}_0 - \tilde{\gamma}'_k\hat{V}^{-1}\tilde{\gamma}_k$.

There is a wide diversity of loss functions available and their properties vary extensively. Even so, all of these share a common feature, in that "lower is better." That is, a large value indicates a poor forecasting performance, whereas a value close to zero implies an almost-perfect forecast. We use three average loss indicators: the Mean Absolute Percentage Error (MAPE), the Adjusted Mean Absolute Percentage Error (AMAPE), and the U-statistic inequality coefficient.

The MAPE and the AMAPE are relative measures, in that they are percentages. In particular, the MAPE is the percentage error, and has the advantage of having a lower bound of zero. Therefore, the lower the indicator the greater the model's forecast accuracy. Nevertheless, this loss function has drawbacks in any practical application. First, with zero values, we have a division by zero issue. Second, the MAPE does not have an upper limit. The AMAPE corrects almost completely the asymmetry problem between actual forecast values and has the advantage of having both a zero lower bound and an upper bound. Like the MAPE, the smaller the AMAPE, the greater the accuracy of predictions.

The U-statistic provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values. The Theil inequality coefficient lies between zero and one, with zero suggesting a perfect fit. It can be decomposed into three sources of inequality: bias, variance, and covariance proportions coverage. The bias component of the forecast errors measures the extent to which the mean of the forecast is different from the mean of the recorded values. Similarly, the variance component tells us how far the variation of the forecast is from the variation of the actual series. Finally, the covariance proportion measures the remaining unsystematic component of the forecasting errors. As expected, the three components add up to one.

4. THE BASIC EMPIRICAL RESULTS

4.1. Fractional Integration Analysis

In Table 2, we present the results of the estimations of the different ARFIMA(ϕ, d, θ) model. The best specifications were selected using the Schwartz Bayesian Information Criterion (BIC) and include statistically significant autoregressive and moving-average terms.

Table 2. Fractional-Integration Results: 1950-2017

Variable	Coefficient	Estimate	Std. Err.	p-value	Significance Interval
Global	α_1	1.640	*0.188*	*0.000*	[1.272 ; 2.008]
	α_2	-0.643	*0.187*	*0.001*	[-1.010 ; -0.276]
	θ_1	-0.512	*0.151*	*0.001*	[-0.808 ; -0.216]
	θ_6	0.262	*0.126*	*0.038*	[0.015 ; 0.509]
	d	**0.270**	***0.144***	***0.060***	**[-0.012 ; 0.552]**
China	α_1	0.980	*0.018*	*0.000*	[0.945 ; 1.015]
	θ_1	0.544	*0.113*	*0.001*	[0.323 ; 0.765]
	d	**0.444**	***0.068***	***0.001***	**[0.311 ; 0.577]**
USA	α_1	0.990	*0.008*	*0.000*	[0.974 ; 1.006]
	d	**0.226**	***0.097***	***0.020***	**[0.036 ; 0.416]**
EU(28)	α_1	0.989	*0.010*	*0.000*	[0.969 ; 1.009]
	d	**0.273**	***0.091***	***0.003***	**[0.095 ; 0.451]**
India	α_1	0.992	*0.009*	*0.000*	[0.974 ; 1.010]
	θ_3	0.558	*0.125*	*0.000*	[0.313 ; 0.803]
	d	**0.322**	***0.078***	***0.000***	**[0.169 ; 0.475]**
Russia	α_1	0.977	*0.022*	*0.000*	[0.934 ; 1.020]
	θ_7	-0.391	*0.143*	*0.002*	[-0.671 ; -0.111]
	d	**0.417**	***0.082***	***0.000***	**[0.256 ; 0.578]**
Japan	α_1	0.985	*0.016*	*0.000*	[0.954 ; 1.016]
	d	***0.299***	***0.099***	***0.002***	**[0.105 ; 0.493]**
ROW	α_1	0.997	*0.004*	*0.000*	[0.989 ; 1.005]
	θ_3	0.415	*0.112*	*0.000*	[0.195 ; 0.635]
	d	**0.193**	***0.071***	***0.007***	**[0.054 ; 0.332]**

Note: $\hat{\alpha}$ stands for the estimated value of the parameter associated with x_{t-p} of the AR component and $\hat{\theta}$ stands for the estimated value of the stochastic term of order q (e_{t-q}) of the MA component.

We perform preliminary tests for the existence of structural breaks for all variables following the procedures in Bai-Perron (2003). Test results suggest the absence of significant evidence for break points. Still, when by simple visual inspection of the data we suspected the possible presence of break points, a dummy variable was included in the ARFIMA models. The corresponding estimated coefficients, however, are never statistically significant and the best specification for ARFIMA models as indicated by the BIC never includes structural breaks.

Our results provide strong empirical evidence for the non-rejection of the presence of long memory for worldwide CO_2 emissions as well as its regional components. The estimated values of the fractional parameter d are all between 0 and 1, thus allowing us to reject both the case of pure stationarity model ($d = 0$) and the case of a unit root model ($d = 1$). All series exhibit long-term memory as all estimated parameters d lie within the interval (0, 0.5).

Total emissions have a degree of persistence of $d = 0.270$ and the degree of fractional integration ranges from a minimum of 0.193 for the ROW to a maximum of 0.444 for China. Furthermore, the degree of persistence we estimate for worldwide emissions corresponds to the exact convex combination of the seven individual regions, which attests to the accuracy of our estimates.

All of the estimates of the fractional integration parameter are statistically significant at 1%. For China and Russia, however, the upper bound is greater than 0.5, leaving open the possibility that CO2 emissions from these countries may be non-stationary, though still mean reverting.

4.2. In-Sample Global CO2 Emissions Forecasts

Figure 1 plots the actual values against the in-sample forecasts for CO_2 emissions between 1950 and 2017 while Table 3 summarizes our forecasting accuracy analysis for the in-sample predictions.

Table 3. In-sample Forecast Accuracy Analysis: 1950-2017

	Global	China	USA	EU(28)	India	Russia	Japan	ROW
Mean Absolute Percentage Error (MAPE)	3.2%	7.9%	4.1%	3.7%	4.2%	4.6%	4.4%	3.4%
Adjusted Mean Absolute Percentage Error (AMAPE)	2.3%	4.8%	2.8%	2.6%	2.9%	3.0%	2.3%	1.7%
Theil Inequality Coefficient	0.02	0.02	0.04	0.03	0.02	0.03	0.02	0.02
Mean Squared Error decomposition:								
Bias proportion	2.0%	1.0%	0.1%	0.4%	0.1%	0.3%	4.0%	11.0%
Variance proportion	0.8%	0.0%	0.0%	0.0%	4.0%	0.0%	2.6%	1.4%
Covariance proportion	97.2%	99.0%	99.9%	99.5%	96.0%	99.7%	93.4%	87.6%

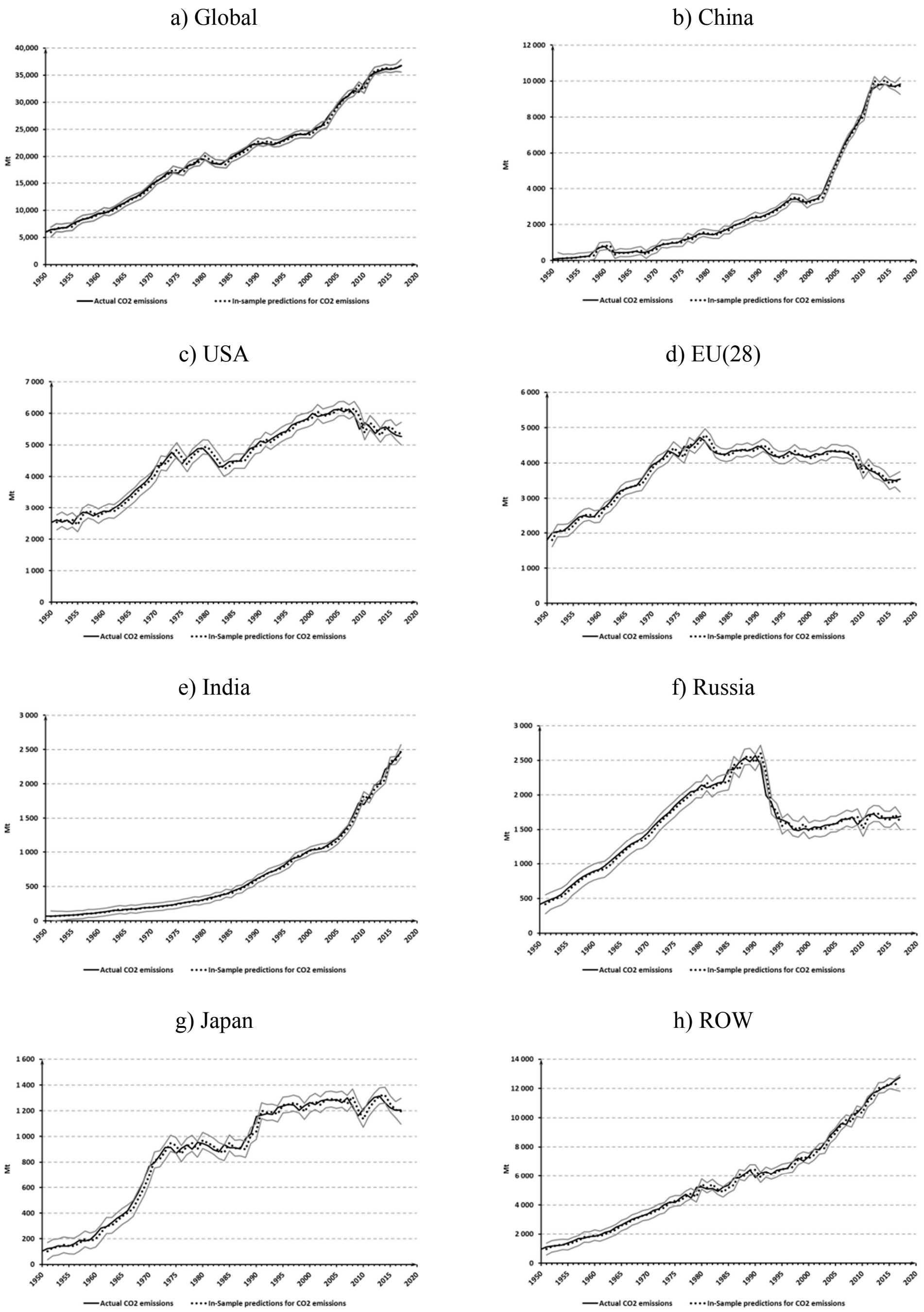

Figure 1. In-sample CO2 Predictions: 1950-2017

We get consistently excellent in-sample predictions with a MAPE ranging from a minimum of 3.2% for worldwide CO_2 emissions to a maximum of 7.9% for emissions from China. The percentage of projected values outside the confidence interval ranges from a minimum of 3% for the USA to a maximum of 7.5% for Japan.

In turn, the U-statistic shows a very small value, varying in a band between 0.02 and 0.04. This suggests that the predictions compare quite well with the observed values. Furthermore, the predictions are non-skewed and show a low variance, which suggests that they closely track the changes in the observed values. In fact, more than 93% of the prediction error in the six countries is non-systematic while for the ROW this component is 87.6%.

Finally, the fact that the degree of persistence we estimate for worldwide CO_2 emissions corresponds to the exact convex combination of the seven individual results guarantees the consistency of the different forecasts. Total projections based on the aggregate results are always very close to the sum of the projections for each of the seven individual components. The difference is, on average, 0.5% in in-sample projections discussed here and about 1.5% in out-of-sample projections discussed below.

5. ARFIMA CO2 EMISSIONS FORECASTS AND THEIR IMPLICATIONS

5.1. The ARFIMA Forecasts 2018 – 2050

Having established a good forecasting performance of the ARFIMA estimates, we use these estimates to forecast CO_2 emissions until 2050. We present the detailed results in Figure 2 while in Table 4 we present summary results relative to 2010 reference levels (the detailed results will be provided upon request to the authors).

We forecast worldwide CO_2 emissions to reach 37,171Mt by 2050 after having reached a peak of 37,623Mt in 2034. The forecasted emission levels in 2030 and 2050 are 12.4% and 11.1% above the 2010 reference level, respectively.

From a national perspective, we can identify two groups of countries in terms of the intertemporal pattern of CO_2 emissions forecasts into 2050. For the first group, emissions are always increasing or reach a peak later in the forecast horizon. This group includes China, India and the ROW, which account for 68.2% of the total emissions in 2017. For the second group, projected emission decline throughout the forecast horizon. This group includes the USA, the EU (28), Russia, and Japan, and accounts for the remaining 31.8% of worldwide emissions.

More specifically for the first group of countries, for China, we forecast CO2 emissions to reach a peak in 2034 at 10,248 Mt. The forecasted levels of emissions in 2030 and 2050 are 20.2% and 18.3% above the 2010 reference level, respectively. For the ROW the projected figures are similar although emissions show a permanently increasing trend. Specifically, the forecast levels of emissions in 2030 and 2050 are 21.4% and 24.9% above the 2010 reference level, respectively.

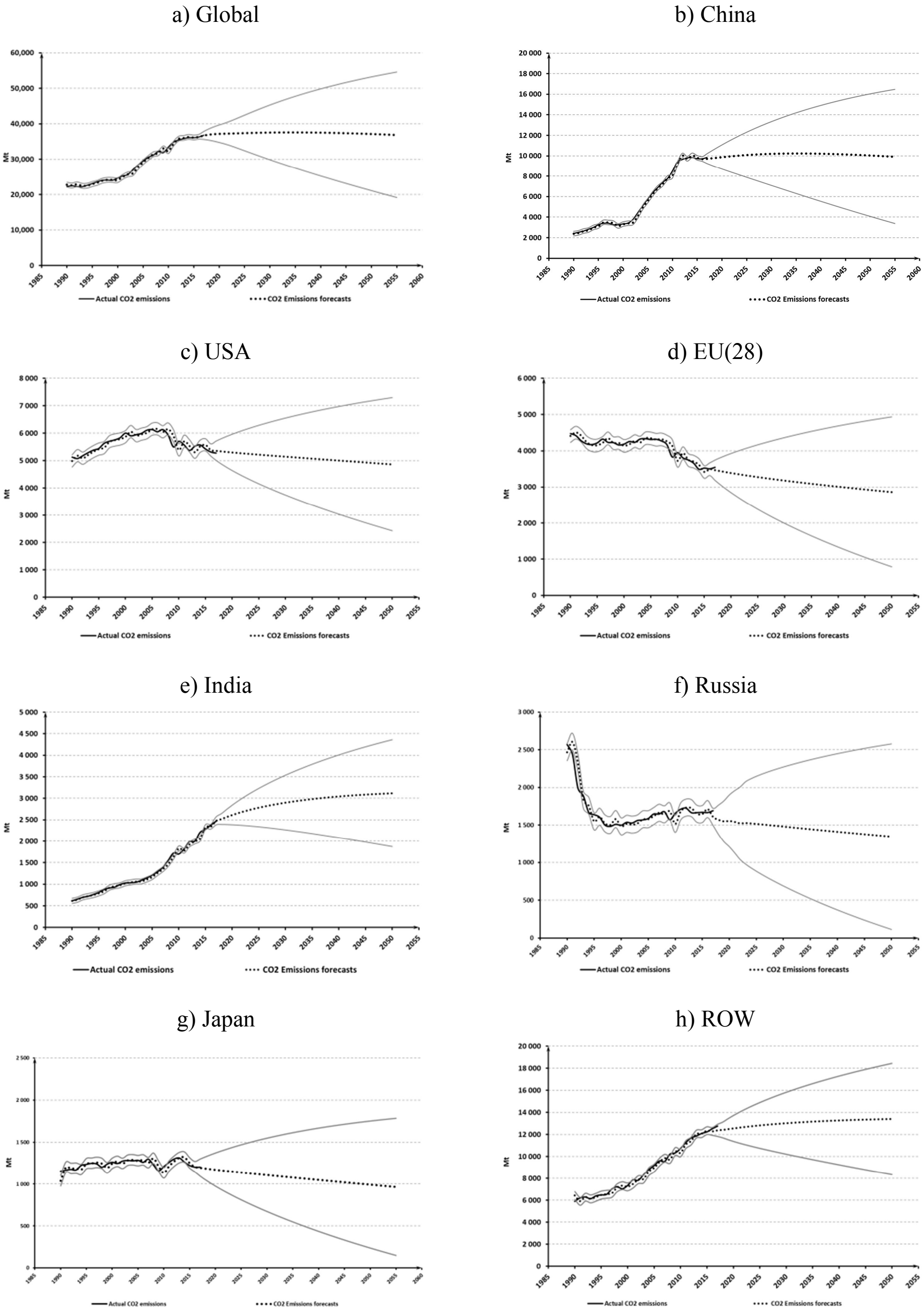

Figure 2. CO2 Emissions Forecasts for 2018 – 2050

Table 4. CO2 Emissions Forecasts Relative to 2010 Reference Levels (%)

	Global	China	USA	EU(28)	India	Russia	Japan	ROW
2020	11.3	16.3	-7.1	-14.2	53.7	-6.1	-3.3	17.0
2030	12.4	20.2	-9.8	-19.5	70.7	-10.7	-8.5	21.4
2040	12.3	20.3	-12.3	-23.8	79.1	-14.9	-13.3	23.7
2050	11.1	18.3	-14.7	-27.5	83.4	-18.8	-18.0	24.9

In turn, we project emissions for India to always be above the 2010 reference levels and increasingly so. By 2030 and 2050, the flow of emissions is respectively 53.7% and 83.4% above the 2010 level. Accordingly, India stands out as a country for which projected emissions show a sharply increasing pattern.

As to the second group of countries, for the USA we project CO2 emissions to be 9.8% and 14.7% below the 2010 emissions levels by 2030 and 2050. For Russia, emissions are projected to be 10.7% and 18.8% below the 2010 levels by 2030 and 2050, respectively while for Japan the projected emissions will be 8.5% and 18.0% below the 2010 level. Finally, for the EU(28) the figures are 19.5% and 27.5% below 2010 level, respectively. Accordingly, the EU(28) stands out as a region showing a slightly more accelerated pattern of decarbonization.

5.2. The ARFIMA Forecasts and the IPCC Special Report 2018 Targets

Under the IPCC targets, global CO2 emissions would have to decrease by 15,050 Mt or 45% of 2010 emissions by 2030 and a further 12,476 Mt, or a further 40% of 2010 levels, between 2030 and 2050. Accordingly, the total target accumulated reduction by 2050 corresponds to a reduction of 85% in emissions relative to 2010 levels.

Of the greatest importance is the comparison of these IPCC policy targets with our ARFIMA CO2 emissions projections. Table 5 shows the policy effort required to meet the new IPCC targets and achieve carbon neutrality by 2050. The first column presents the total effort necessary to achieve the intermediate IPCC target for 2030 while the second column displays the total effort necessary by 2050 to achieve carbon neutrality. The difference between the ARFIMA forecasts and the IPCC figures in the first row, therefore, measures the additional/reduced effort implied by the ARFIMA forecasts to reach the IPCC targets. In Figure 3, we provided a panoramic view of the two relevant trajectories.

Our results indicate that to meet the IPCC mid-term targets in 2030, it is necessary a worldwide policy effort that leads to a reduction of CO2 emissions of 57.4% relative to 2010 levels. Of these, 12.4% corresponds to the extra effort over the basic 45% IPCC reduction target due to the inertia of the emissions system. To achieve carbon neutrality by 2050 will require a total reduction of CO2 emissions of 97.4% of 2010 levels.

Table 5. Reductions in CO2 Emissions Relative to 2010 (%)

	2030	2050
IPCC (2018) targets	-45.0	-85.0
Policy effort based on ARFIMA forecasts		
Global	-57.4	-97.4
China	-65.2	-105.2
USA	-35.2	-75.1
EU(28)	-25.5	-65.8
India	-115.7	-156.0
Russia	-34.3	-74.3
Japan	-36.5	-76.7
ROW	-71.4	-111.4

These forecasts imply that the policy efforts required to achieve decarbonization are very large, substantially larger than indicated by the IPCC targets themselves. Furthermore, they are also frontloaded. In the next decade emissions need to decline by more than the two following decades. This frontloading clearly exceeds the frontloading already contemplated in the IPCC targets.

Naturally, these aggregate results hide very different realities. For regions such as China, ROW, and India, the task is larger than these worldwide numbers indicate while for the remaining countries the opposite is true.

For China, a policy effort that cuts CO2 emissions by 65.2% of 2010 levels by 2030 is necessary to meet IPCC targets. By 2050, a reduction of emissions equivalent to 105.2% of the 2010 emissions is required. For China, the policy effort in somewhat larger than the effort measured at the aggregate level and about equally as frontloaded. A similar situation both qualitatively and quantitatively applies to the ROW. This means policy efforts needed to achieve the IPCC goals in these two blocks are close to worldwide standards.

The case of India, however, deserves a closer look as the policy efforts necessary to achieve the IPCC CO2 emissions targets are much more pronounced. By 2030, these policy efforts would have to lead to a reduction of 115.7% of 2010 levels while by 2050 the reduction would have to be 156% of such levels. Therefore, the policy efforts for decarbonization in India are rather imposing. Furthermore, they are substantially more frontloaded than the worldwide average.

On the other side of this divide are the USA, EU(28), Russia, and Japan, for which the inertia of the emissions system suggests that the policy efforts needed to promote the decarbonisation are lower than the IPCC goals themselves. In particular, for the EU(28) our results suggest that policy efforts leading to 25.5% and 65.8% reduction in emissions relative to 2010 levels would be needed by 2030 and 2050, respectively. Furthermore, such efforts are also substantially less frontloaded. For the remaining countries, the same qualitative patterns apply albeit requiring a slightly stronger policy effort. For USA, Russia and Japan, the policy efforts necessary to achieve the IPCC 2030 targets are just over one-third of the 2010 emissions: 35.2%, 34.3% and 36.5%, respectively. By 2050, they are about three-quarters of 2010 emissions: 75.1%, 74.3%, and 76.7%, respectively.

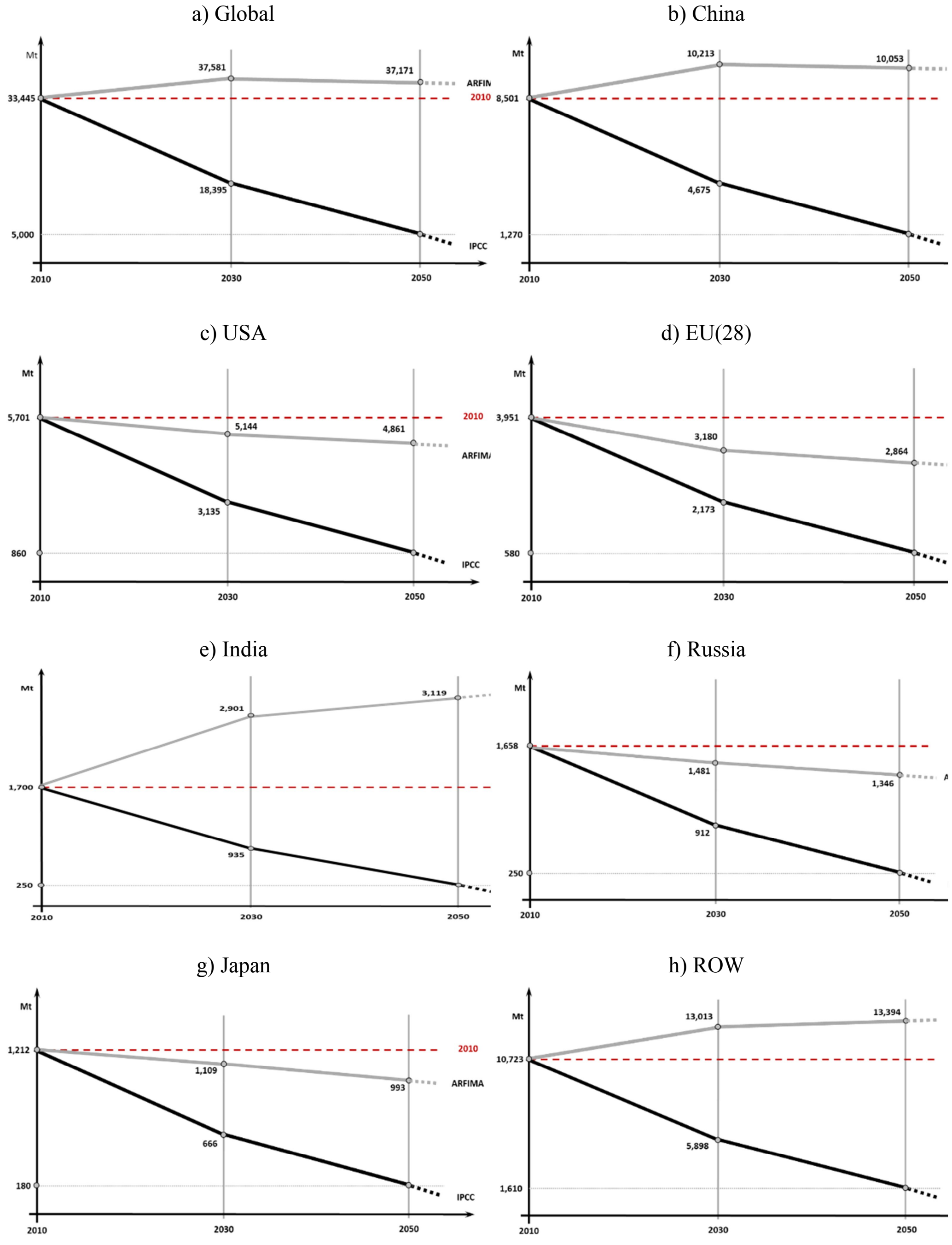

Figure 3. CO2 Emissions: ARFIMA Projections versus IPCC Goals

6. SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS

This work uses an ARFIMA model to evaluate the degree of persistence of worldwide CO_2 emissions. Our empirical results suggest that emissions, both worldwide and for each of the seven regions considered, are fractionally integrated processes. Accordingly, the different series show long-memory and the effects of shocks tend to dissipate at a slow hyperbolic rate. Our results also suggest that the emissions from the ROW exhibit the weakest degree of long-range dependence, while emissions from China and Russia have the strongest levels of persistence.

The long-memory nature of the emissions data implies that any policy shock will have temporary effects albeit longer lasting than suggested in a traditional analysis of stationarity. The mean reversal property of our estimates, however, implies that the policy effort must be persistent to produce equally persistent effects. This is particularly relevant in the framework of the international strategies for achieving carbon neutrality in 2050 where it will be crucial to promote permanent changes in behavior.

In terms of the CO_2 emissions projections, our approach uses only the information included in the stochastic process underlying the baseline data, in a context in which the existing policies remain invariant. From a regional perspective, our projections suggest that emissions from China, India and the ROW show a growing pattern into the future. For China emissions will peak around 2034 while for India and the ROW emission will peak after the our forecast horizon. Conversely, for the remaining regions, the USA, the EU(28), Russia, and Japan, projections show a declining pattern of emissions. Of these, the EU (28) achieves the largest percentage reduction in its annual flow under our reference forecasts.

Significantly, our results clearly suggest that the underlying inertia of the emissions systems is insufficient to generate a path of emissions consistent with the intermediate IPCC target for 2030 or with the goal of carbon neutrality by 2050. In fact, they suggest quite the opposite as we actually project in several cases CO_2 emissions by 2030 and 2050 increasingly above 2010 levels.

We measure the policy efforts necessary as the difference between the reductions of CO_2 emissions required to achieve the IPCC targets and the evolution of emissions as measured by the underling ARFIMA inertial projections. For worldwide emissions, the aggregate effort by 2050 is equivalent to 97.4% of 2010 emissions. This policy effort is frontloaded as about 60% of such efforts would have to occur before 2030.

Our results suggest that in order to achieve such policy targets in the USA, EU(28), Russia, and Japan, which account for just about 40% of worldwide emissions, the policy efforts required are lower than the IPCC goals themselves. Specifically, our results suggest that by 2050, policy efforts would have to lead to reductions of 75.1%, 65.8%, 76.7%, and 74.3% of 2010 levels. In addition, these policy efforts are clearly less frontloaded than the worldwide patterns as only around 45% of the policy efforts would have to occur before 2030. In the case of the EU(28), policy efforts required are less pronounced and less frontloaded than in the other three regions.

In the case of China, India and the ROW, which account for about 60% of worldwide emissions, additional deliberate policy efforts are necessary leading by 2050 to reductions in emissions of 105.0%, 156.0% and 111.4%, of the 2010 levels, respectively. The case of India is to be highlighted as policy efforts are not only rather severe but also rather dramatically frontloaded as about 74% of the policy efforts would have to occur by 2030.

Our results suggest that the policies toward decarbonization of the economy by 2050 be tailored considering the specific characteristics of each one of the different regional components of worldwide CO_2 emissions. Given the differences in the inertia of emissions in the different regions a one-size fits all approach may not be the best approach. More specifically, our results provide insights into each region's required contribution towards meeting the IPCC targets. In fact, the contribution of the four regions – the USA, the EU(28), Russia and Japan, whose emissions trajectories are decreasing represent 33.9% of worldwide emissions but are expected to contribute with only 20.0% of the emissions reductions necessary by 2030. The opposite is true for China, India, and ROW for whom meeting the IPCC targets by 2030 will mean a reduction of 28.9% and 10.3%, and 39.9% of total emissions, respectively while they represent 26.8%, 5.8% and 33.4% of emissions. In this sense, trading off emission reductions among these regions maybe an optimal strategy.

Lastly, consider the fact that the economic and societal impacts of climate change - on productivity, water resources, transport, energy production and consumption, migration, tourism and leisure, infrastructure, food production capacity, well-being and public health, migration, biodiversity and even political stability - are still far from being fully identified and much less internalized into policy decision making [see Tol (2018)].

Our results contribute to strengthening the need to define and implement transition, adaptation and mitigation policies climate and energy, consistent with the goal of carbon neutrality in 2050, fully aligned with both the goals of the Paris Agreement and the United Nations Sustainable Development Goals. Such policies are urgent, daunting and frontloaded. They cannot also be of a one-size-fits-all type across different regions of the world. In this sense, our work is a contribution to the ongoing debate on how different regions can or should contribute towards the common goals of achieving carbon neutrality by 2050 as postulated by the IPCC 2018 targets.

APPENDIX

Table A1. Worldwide CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	36,990	10.6	975	2.6	35,387	38,594
2019	37,141	11.1	1,243	3.3	35,096	39,186
2020	37,214	11.3	1,502	4.0	34,743	39,684
2021	37,255	11.4	1,752	4.7	34,374	40,136
2022	37,295	11.5	2,045	5.5	33,931	40,660
2023	37,338	11.6	2,368	6.3	33,442	41,233
2024	37,381	11.8	2,706	7.2	32,930	41,832
2025	37,423	11.9	3,049	8.1	32,408	42,437
2026	37,463	12.0	3,390	9.0	31,886	43,039
2027	37,499	12.1	3,727	9.9	31,369	43,629
2028	37,531	12.2	4,057	10.8	30,857	44,204
2029	37,558	12.3	4,380	11.7	30,353	44,763
2030	37,581	12.4	4,696	12.5	29,857	45,305
2031	37,599	12.4	5,004	13.3	29,368	45,829
2032	37,612	12.5	5,304	14.1	28,887	46,336
2033	37,620	12.5	5,597	14.9	28,413	46,827
2034	37,623	12.5	5,884	15.6	27,945	47,301
2035	37,622	12.5	6,164	16.4	27,483	47,761
2036	37,617	12.5	6,438	17.1	27,028	48,206
2037	37,607	12.4	6,706	17.8	26,577	48,637
2038	37,593	12.4	6,968	18.5	26,132	49,054
2039	37,576	12.4	7,225	19.2	25,692	49,459
2040	37,554	12.3	7,477	19.9	25,257	49,852
2041	37,530	12.2	7,724	20.6	24,826	50,234
2042	37,502	12.1	7,966	21.2	24,399	50,604
2043	37,470	12.0	8,204	21.9	23,976	50,964
2044	37,436	11.9	8,437	22.5	23,557	51,314
2045	37,398	11.8	8,667	23.2	23,142	51,654
2046	37,358	11.7	8,893	23.8	22,731	51,985
2047	37,315	11.6	9,114	24.4	22,323	52,307
2048	37,270	11.4	9,332	25.0	21,919	52,620
2049	37,222	11.3	9,547	25.6	21,518	52,925
2050	37,171	11.1	9,758	26.3	21,121	53,222

Table A2. China CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	9 781	15.1	436	4.5	9 064	10 497
2019	9 833	15.7	576	5.9	8 886	10 781
2020	9 886	16.3	712	7.2	8 715	11 056
2021	9 935	16.9	843	8.5	8 548	11 322
2022	9 982	17.4	971	9.7	8 384	11 579
2023	10 024	17.9	1 096	10.9	8 222	11 826
2024	10 063	18.4	1 217	12.1	8 061	12 065
2025	10 097	18.8	1 336	13.2	7 900	12 294
2026	10 128	19.1	1 452	14.3	7 740	12 515
2027	10 155	19.5	1 565	15.4	7 580	12 729
2028	10 178	19.7	1 676	16.5	7 421	12 934
2029	10 197	20.0	1 784	17.5	7 262	13 132
2030	10 213	20.2	1 891	18.5	7 104	13 323
2031	10 227	20.3	1 995	19.5	6 946	13 507
2032	10 237	20.4	2 096	20.5	6 788	13 685
2033	10 244	20.5	2 196	21.4	6 631	13 856
2034	10 248	20.6	2 294	22.4	6 474	14 022
2035	10 250	20.6	2 390	23.3	6 318	14 182
2036	10 249	20.6	2 484	24.2	6 163	14 336
2037	10 247	20.5	2 577	25.1	6 008	14 485
2038	10 242	20.5	2 667	26.0	5 855	14 629
2039	10 235	20.4	2 756	26.9	5 702	14 768
2040	10 226	20.3	2 843	27.8	5 549	14 902
2041	10 215	20.2	2 929	28.7	5 398	15 032
2042	10 203	20.0	3 013	29.5	5 247	15 158
2043	10 189	19.9	3 095	30.4	5 098	15 280
2044	10 173	19.7	3 176	31.2	4 949	15 397
2045	10 156	19.5	3 255	32.1	4 802	15 511
2046	10 138	19.3	3 333	32.9	4 655	15 621
2047	10 118	19.0	3 410	33.7	4 509	15 727
2048	10 098	18.8	3 485	34.5	4 365	15 830
2049	10 076	18.5	3 559	35.3	4 221	15 930
2050	10 053	18.3	3 632	36.1	4 079	16 027

Table A3. USA CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	5 336	-6.4	284	5.3	4 868	5 803
2019	5 316	-6.8	346	6.5	4 746	5 885
2020	5 298	-7.1	404	7.6	4 634	5 962
2021	5 280	-7.4	458	8.7	4 527	6 033
2022	5 264	-7.7	509	9.7	4 426	6 101
2023	5 248	-8.0	558	10.6	4 330	6 166
2024	5 232	-8.2	605	11.6	4 237	6 227
2025	5 217	-8.5	650	12.5	4 147	6 286
2026	5 202	-8.8	694	13.3	4 061	6 343
2027	5 187	-9.0	736	14.2	3 976	6 398
2028	5 173	-9.3	777	15.0	3 894	6 451
2029	5 158	-9.5	817	15.8	3 814	6 502
2030	5 144	-9.8	856	16.6	3 736	6 552
2031	5 129	-10.0	894	17.4	3 660	6 599
2032	5 115	-10.3	931	18.2	3 585	6 646
2033	5 101	-10.5	967	18.9	3 511	6 691
2034	5 087	-10.8	1 002	19.7	3 439	6 735
2035	5 073	-11.0	1 036	20.4	3 368	6 777
2036	5 059	-11.3	1 070	21.1	3 299	6 818
2037	5 045	-11.5	1 103	21.9	3 231	6 859
2038	5 030	-11.8	1 135	22.6	3 163	6 898
2039	5 016	-12.0	1 167	23.3	3 097	6 936
2040	5 002	-12.3	1 198	23.9	3 032	6 973
2041	4 988	-12.5	1 229	24.6	2 967	7 009
2042	4 974	-12.8	1 259	25.3	2 904	7 044
2043	4 960	-13.0	1 288	26.0	2 841	7 078
2044	4 946	-13.2	1 317	26.6	2 780	7 112
2045	4 932	-13.5	1 345	27.3	2 719	7 145
2046	4 917	-13.7	1 373	27.9	2 659	7 176
2047	4 903	-14.0	1 401	28.6	2 599	7 207
2048	4 889	-14.2	1 428	29.2	2 541	7 238
2049	4 875	-14.5	1 454	29.8	2 483	7 267
2050	4 861	-14.7	1 481	30.5	2 425	7 296

Table A4. EU(28) CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	3 441	-12.9	228	6.6	3 065	3 816
2019	3 414	-13.6	281	8.2	2 952	3 876
2020	3 389	-14.2	330	9.7	2 846	3 931
2021	3 365	-14.8	376	11.2	2 746	3 983
2022	3 341	-15.4	420	12.6	2 650	4 033
2023	3 319	-16.0	463	13.9	2 558	4 080
2024	3 298	-16.5	504	15.3	2 469	4 126
2025	3 277	-17.1	543	16.6	2 384	4 170
2026	3 256	-17.6	581	17.8	2 301	4 212
2027	3 237	-18.1	618	19.1	2 220	4 253
2028	3 217	-18.6	654	20.3	2 142	4 292
2029	3 198	-19.1	688	21.5	2 066	4 331
2030	3 180	-19.5	722	22.7	1 992	4 368
2031	3 162	-20.0	755	23.9	1 920	4 404
2032	3 144	-20.4	787	25.0	1 849	4 439
2033	3 127	-20.9	818	26.2	1 780	4 473
2034	3 110	-21.3	849	27.3	1 713	4 506
2035	3 093	-21.7	879	28.4	1 647	4 539
2036	3 076	-22.1	908	29.5	1 582	4 570
2037	3 060	-22.6	937	30.6	1 519	4 601
2038	3 044	-23.0	965	31.7	1 457	4 631
2039	3 028	-23.4	992	32.8	1 396	4 660
2040	3 012	-23.8	1 019	33.8	1 336	4 688
2041	2 997	-24.2	1 045	34.9	1 277	4 716
2042	2 981	-24.5	1 071	35.9	1 220	4 743
2043	2 966	-24.9	1 096	37.0	1 163	4 769
2044	2 951	-25.3	1 121	38.0	1 107	4 795
2045	2 936	-25.7	1 145	39.0	1 052	4 820
2046	2 922	-26.1	1 169	40.0	998	4 845
2047	2 907	-26.4	1 193	41.0	945	4 869
2048	2 893	-26.8	1 216	42.0	893	4 892
2049	2 878	-27.2	1 238	43.0	841	4 915
2050	2 864	-27.5	1 261	44.0	791	4 938

Table A5. India CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	2 520	48.2	77	3.0	2 393	2 646
2019	2 569	51.1	108	4.2	2 391	2 747
2020	2 613	53.7	139	5.3	2 385	2 841
2021	2 654	56.1	167	6.3	2 378	2 929
2022	2 691	58.3	195	7.3	2 370	3 012
2023	2 725	60.3	222	8.1	2 360	3 089
2024	2 756	62.1	247	9.0	2 349	3 162
2025	2 785	63.8	272	9.8	2 337	3 232
2026	2 811	65.4	296	10.5	2 324	3 299
2027	2 836	66.8	320	11.3	2 310	3 362
2028	2 859	68.2	343	12.0	2 296	3 423
2029	2 881	69.5	365	12.7	2 280	3 482
2030	2 901	70.7	387	13.3	2 265	3 538
2031	2 920	71.8	409	14.0	2 248	3 593
2032	2 938	72.8	430	14.6	2 231	3 645
2033	2 955	73.8	450	15.2	2 214	3 696
2034	2 970	74.7	471	15.8	2 196	3 745
2035	2 985	75.6	491	16.4	2 178	3 792
2036	2 999	76.4	510	17.0	2 159	3 838
2037	3 012	77.2	530	17.6	2 140	3 883
2038	3 024	77.9	549	18.1	2 121	3 926
2039	3 035	78.5	567	18.7	2 102	3 968
2040	3 046	79.1	586	19.2	2 082	4 009
2041	3 055	79.7	604	19.8	2 062	4 049
2042	3 065	80.3	622	20.3	2 042	4 087
2043	3 073	80.8	639	20.8	2 022	4 125
2044	3 081	81.3	657	21.3	2 001	4 162
2045	3 089	81.7	674	21.8	1 980	4 197
2046	3 096	82.1	691	22.3	1 959	4 232
2047	3 102	82.5	707	22.8	1 938	4 266
2048	3 108	82.8	724	23.3	1 917	4 299
2049	3 114	83.2	740	23.8	1 896	4 331
2050	3 119	83.4	756	24.2	1 875	4 363

Table A6. Russia CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	1 572	-5.2	119	7.6	1 375	1 768
2019	1 551	-6.5	166	10.7	1 278	1 824
2020	1 556	-6.1	210	13.5	1 210	1 902
2021	1 544	-6.9	253	16.4	1 128	1 960
2022	1 524	-8.1	294	19.3	1 040	2 008
2023	1 528	-7.8	334	21.8	979	2 077
2024	1 523	-8.1	361	23.7	930	2 117
2025	1 517	-8.5	385	25.3	884	2 149
2026	1 510	-8.9	406	26.9	842	2 178
2027	1 503	-9.3	426	28.4	802	2 204
2028	1 496	-9.8	445	29.8	763	2 228
2029	1 488	-10.2	464	31.2	725	2 251
2030	1 481	-10.7	481	32.5	689	2 273
2031	1 474	-11.1	498	33.8	654	2 294
2032	1 466	-11.5	515	35.1	620	2 313
2033	1 459	-12.0	531	36.4	586	2 332
2034	1 452	-12.4	546	37.6	553	2 351
2035	1 445	-12.8	562	38.9	522	2 369
2036	1 438	-13.2	576	40.1	490	2 386
2037	1 431	-13.7	591	41.3	460	2 403
2038	1 424	-14.1	605	42.4	430	2 419
2039	1 417	-14.5	618	43.6	401	2 434
2040	1 411	-14.9	632	44.8	372	2 449
2041	1 404	-15.3	645	45.9	344	2 464
2042	1 397	-15.7	657	47.0	316	2 478
2043	1 391	-16.1	670	48.2	289	2 492
2044	1 384	-16.5	682	49.3	263	2 506
2045	1 378	-16.9	694	50.4	237	2 519
2046	1 371	-17.3	705	51.4	211	2 531
2047	1 365	-17.6	717	52.5	186	2 544
2048	1 359	-18.0	728	53.6	162	2 556
2049	1 353	-18.4	739	54.6	138	2 568
2050	1 346	-18.8	749	55.7	114	2 579

Table A7. Japan CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	1 188	-2.0	83	6.9	1 052	1 323
2019	1 180	-2.6	102	8.6	1 012	1 347
2020	1 172	-3.3	120	10.3	974	1 370
2021	1 165	-3.8	138	11.8	939	1 391
2022	1 158	-4.4	154	13.3	905	1 412
2023	1 152	-4.9	170	14.7	872	1 431
2024	1 146	-5.4	185	16.2	841	1 450
2025	1 139	-6.0	200	17.5	811	1 468
2026	1 133	-6.5	214	18.9	781	1 485
2027	1 127	-7.0	228	20.2	753	1 501
2028	1 121	-7.5	241	21.5	725	1 517
2029	1 115	-8.0	254	22.7	698	1 532
2030	1 109	-8.5	266	24.0	671	1 547
2031	1 103	-8.9	278	25.2	645	1 561
2032	1 097	-9.4	290	26.4	620	1 574
2033	1 091	-9.9	302	27.6	595	1 587
2034	1 085	-10.4	313	28.8	571	1 600
2035	1 080	-10.9	324	30.0	547	1 612
2036	1 074	-11.4	334	31.1	524	1 624
2037	1 068	-11.9	345	32.3	501	1 635
2038	1 062	-12.3	355	33.4	478	1 646
2039	1 056	-12.8	365	34.5	456	1 656
2040	1 050	-13.3	374	35.6	435	1 666
2041	1 045	-13.8	384	36.7	413	1 676
2042	1 039	-14.3	393	37.8	392	1 685
2043	1 033	-14.7	402	38.9	372	1 695
2044	1 027	-15.2	411	40.0	351	1 703
2045	1 022	-15.7	420	41.1	332	1 712
2046	1 016	-16.1	428	42.1	312	1 720
2047	1 010	-16.6	436	43.2	293	1 728
2048	1 005	-17.1	444	44.2	274	1 736
2049	999	-17.5	452	45.3	255	1 743
2050	993	-18.0	460	46.3	236	1 750

Table A8. ROW CO2 Emissions Forecasts for 2018-2050

Years	Total co2 emissions (forecasts - f_t)	Distançe to reference year (2010)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	12 408	15.7	435	3.5	11 692	13 124
2019	12 476	16.4	581	4.7	11 520	13 433
2020	12 543	17.0	715	5.7	11 367	13 718
2021	12 605	17.5	838	6.6	11 227	13 983
2022	12 663	18.1	953	7.5	11 096	14 230
2023	12 717	18.6	1 061	8.3	10 972	14 462
2024	12 768	19.1	1 164	9.1	10 853	14 683
2025	12 816	19.5	1 263	9.9	10 739	14 893
2026	12 860	19.9	1 358	10.6	10 627	15 093
2027	12 902	20.3	1 449	11.2	10 518	15 286
2028	12 941	20.7	1 538	11.9	10 412	15 471
2029	12 978	21.0	1 624	12.5	10 308	15 649
2030	13 013	21.4	1 707	13.1	10 205	15 821
2031	13 046	21.7	1 789	13.7	10 104	15 988
2032	13 077	21.9	1 868	14.3	10 004	16 149
2033	13 105	22.2	1 946	14.8	9 905	16 306
2034	13 133	22.5	2 022	15.4	9 807	16 458
2035	13 158	22.7	2 096	15.9	9 711	16 606
2036	13 182	22.9	2 169	16.5	9 615	16 749
2037	13 205	23.1	2 240	17.0	9 520	16 890
2038	13 226	23.3	2 310	17.5	9 426	17 026
2039	13 246	23.5	2 379	18.0	9 333	17 159
2040	13 265	23.7	2 447	18.4	9 240	17 289
2041	13 282	23.9	2 513	18.9	9 148	17 416
2042	13 298	24.0	2 579	19.4	9 057	17 540
2043	13 314	24.2	2 643	19.9	8 966	17 661
2044	13 328	24.3	2 707	20.3	8 876	17 780
2045	13 341	24.4	2 769	20.8	8 787	17 896
2046	13 353	24.5	2 831	21.2	8 697	18 010
2047	13 365	24.6	2 891	21.6	8 609	18 121
2048	13 375	24.7	2 951	22.1	8 521	18 230
2049	13 385	24.8	3 010	22.5	8 433	18 337
2050	13 394	24.9	3 069	22.9	8 346	18 442

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Received July 11, 2020, Revised June 21, 2021, Accepted June 30, 2021.