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Original Paper

ARFIMA Reference Forecasts for Worldwide CO_2 Emissions and the Need for Large and Frontloaded Decarbonization Policies

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Abstract

We provide reference forecasts for worldwide CO2 emissions from fuel fossil combustion and cement production based on an ARFIMA approach. Our projections suggest that for the IPCC goals to be achieved it is necessary to reduce emissions by 57.4% and 97.4% of 2010 emissions by 2030 and 2050, respectively. Furthermore, the bulk of these efforts have to take place by 2030. Finally, the presence in the data of long memory suggests that policies must be persistent to ensure permanent reductions in emissions. These results add to the sense of urgency in dealing with the issue of decarbonization.

Keywords

Worldwide CO_2 emissions, IPCC emission targets, long memory, ARFIMA

1. Introduction

The purpose of this article is to provide reference forecasts for worldwide CO_2 emissions based on an ARFIMA approach. We consider both aggregate emissions and each of its main sources – solid fuels, liquid fuels, gas, gas flaring, and cement production. Our ultimate objective is to compare our reference forecasts with the recent IPCC emissions targets and thereby ascertain the nature of the policy efforts necessary 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 (see IPCC, 2014).

Recently, the IPCC (2018) report has pointed that limiting global warming to 1.5 ℃ would require "rapid and far-reaching" transitions in land, energy, industry, buildings, transport, and cities. Global net anthropogenic emissions of CO_2 would need to fall by about 45% from 2010 levels by 2030, reaching "net zero" by 2050. As the IPCC suggests that the natural carbon sequestration capacity will be approximately 15% of the 2010 levels, carbon neutrality implies by 2050 a reduction of 85% relative to 2010 levels.

The question remains, however, as to the magnitude and timing of the policy efforts necessary to achieve such policy targets. In turn, identifying the proper reference scenario is critical first step in ascertaining the extent of the policy effort required, and thereby determining the costs involved in achieving such goals.

Specifying a reference scenario, as in the typical "business as usual" projections, means predicting a path to CO_2 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 CO_2 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 rooted on the most basic statistical fundamentals of the stochastic processes that underlie 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 CO_2emissions (See Belbute & Pereira, 2015, 2017).

There is now an extensive literature on fractional integration, which considers the possibility that variables may follow a long memory process (see, among others, Diebold & Rudebusch, 1991; Lo, 1991; Sowell, 1992a; Palma, 2007). The ARFIMA methodology is inspired by a budding literature on the analysis of energy and CO_2emissions based on a fractional integration approach (see, for example, Barassi et al., 2011; Apergis & Tsoumas, 2011, 2012; Barros et al., 2016; Gil-Alana et al., 2015; Belbute & Pereira, 2015, 2017).

The fractional integration approach goes well beyond the stationary/non-stationary 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 means a significant dependence between observations widely separated in time, and, therefore, the effects of policy shocks may be temporary but long lasting.

Measuring the persistence of CO_2 emissions is of utmost importance for the specification of long-term reference case scenarios for emissions as well as 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. Long memory is an intermediate case in which the policy stance needs to be steady but the effects of transitory policies are long lasting.

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 CO_2 emissions for the period between 1950 and 2017. The data until 2014 is from the Carbon-Dioxide Information Analysis Centre (see Boden et al., 2017). This data set contains information going back to 1870. Nevertheless, in this work we have elected to work only with data starting in 1950, given the profound structural changes that occurred after World War II. In turn, data for 2015-2017 is from the national emissions inventories collected by the United Nations (see UNFCCN, 2018) and reported by Global Carbon Atlas (2019).

Aggregate CO_2 emissions are the sum of five components: emissions from burning fossil fuels – solid, liquid, gas, and gas flaring, and emissions from cement production. The data do not consider emissions from land use, nor from land-use change and forestry. 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.

2.2 Description of the Data

Table 1 presents summary information about our data. The first column shows the value of the global CO_2 emissions in the first year of each decade while the remaining columns show the mean shares in total emissions for the decade of each of the emissions sources.

Over the sample period, worldwide CO_2 emissions grew consistently. Nevertheless, we can identify two distinct periods. Between 1950 and 1980, global emissions grew at an annual average rate of 4.1%, reaching 19,628.1 Mt in 1979. More recently, the average annual growth rate fell to 1.7%. By 2017, emissions reached their highest value ever at 36,767 Mt, a value that is 10% above the 2010 levels.

Combustion of solid fuels was the dominant source of CO_2 emissions during the first two decades of our sample period, contributing on average to around 53.5% of total emissions. In 2017, however, this figure was just 39.6% of total emissions. Over the sample period, the emissions from fossil fuel combustion averaged 38.9% of total emissions.

Combustion of liquid fuels accounted on average for 37.7% for total CO_2 emissions over the sample period. In the first three decades, this share increased from 29.7% in the 1950s to 47.2% in the 1970s. Since 1980, however, it declined reaching 34.4% in 2017.

CO_2 emissions from gas represent 17.9% of total emissions over the sample period. In the 1950s they were 7.3% of emissions and increased to 12.9% in the 1970s. In subsequent decades, the relative importance of these emissions continuously increased although at a slower pace. In 2017, they reached their highest value with 19.6% of total emissions.

CO_2 emissions from cement production account for 3.2% of total emissions over the sample period. The relative share of emissions from cement production showed a persistently increasing pattern reaching 5.7% in 2017. Finally, CO_2 emissions from gas flaring account for 1.0% of total emissions over the sample period. After 1980s, the relative share of CO_2 emissions from gas flaring declined to reach 0.7% in 2017.

Table 1. Global CO_2 Emissions from Fossil Fuel Combustion and Cement Production

Worldwide CO_2 Emissions		**Average Shares of Total Emissions (%)**					
Years	**Mt**	**Years**	**Solid Fuels**	**Liquid Fuels**	**Gas Fuels**	**Cement Production**	**Gas Flaring**
1950	5 972.32	**1950-1959**	60.2	29.7	7.3	1.4	1.5
1960	9 412.82	**1960-1969**	46.9	38.9	10.6	1.9	1.8
1970	14 850.19	**1970-1979**	35.7	47.2	12.9	2.1	2.1
1980	19 422.86	**1980-1989**	39.4	42.1	15.1	2.4	1.0
1990	22 255.14	**1990-1999**	36.9	41.3	18.1	3.0	0.6
2000	24 669.71	**2000-2009**	38.1	38.5	18.7	4.0	0.7
2010	33 444.99	**2010-2017**	41.4	33.6	18.8	5.5	0.7
2017	36 767.15	**2017**	39.6	34.4	19.6	5.7	0.7
1950-2017		**1950-2017**	38.9	37.7	17.9	3.2	1.0

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

$$(1-L)^d x_t = u_t, \qquad t = 1, 2, 3, \ldots \tag{1}$$

where, β is the coefficients vector, z_t represents all deterministic factors of the process, y_t, and $t = 1, 2, \ldots n$, 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 an extra flexibility that may be important when modeling long-term dependence in the conditional mean. 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 can be called anti-persistent, or, alternatively, to have rebounding behavior or 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. Nevertheless, 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 & Joyeux, 1980; Granger, 1980, 1981; Sowell, 1992a, 1992b; Baillie, 1996; Palma, 2007; Hassler et al., 2016; Belbute & 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 & Mikkelsen, 1996).

If the process $\{u_t\}$ in (1) is an $ARMA(p,q)$, 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

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

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

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

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 $\boldsymbol{D} = \text{Diag}(v_t)$ and $\boldsymbol{L}$ is lower triangular, so that;

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

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

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

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 $MSE\big(\hat{f}_{T+k}\big) = \hat{\gamma}_0 - \widetilde{\gamma'}_k\hat{V}^{-1}\tilde{\gamma}_k$.

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-statist 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. he 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

We present in Table 2, the results of the estimations of the ARFIMA(ϕ, d, θ) models. 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

Variable	Coefficient	Estimates	Std. Err.	p-value	Significance interval	BIC
Total CO_2 Emissions	α_1	1.640	*0.188*	*0.000*	[1.272 ; 2.008]	*1,044.96*
	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]**	
CO_2 Emissions from Solid Fuels	α_1	0.952	*0.031*	*0.000*	[0.891 ; 1.013]	950.35
	θ_7	0.508	*0.178*	*0.004*	[0.159 ; 0.857]	
	d	**0.471**	***0.041***	***0.000***	**[0.391 ; 0.551]**	
CO_2 Emissions from Liquid Fuels	α_1	0.992	*0.010*	*0.000*	[0.972 ; 1.012]	*961.85*
	θ_3	0.249	*0.108*	*0.021*	[0.037 ; 0.461]	
	d	**0.285**	***0.093***	***0.002***	**[0.103 ; 0.467]**	
CO_2 Emissions from Gas Fuels	α_1	0.997	*0.004*	*0.000*	[0.989 ; 1.005]	*829.14*
	α_3	0.123	*0.124*	*0.323*	[-0.120 ; 0.366]	
	d	**0.314**	***0.067***	***0.000***	**[0.183 ; 0.445]**	
CO_2 Emissions from Cement Production	α_1	0.975	*0.018*	*0.000*	[0.940 ; 1.010]	*654.66*
	α_7	0.673	*0.140*	*0.002*	[0.399 ; 0.947]	
	d	**0.470**	***0.040***	***0.000***	**[0.392 ; 0.548]**	
CO_2 Emissions from Gas Flaring	α_1	0.970	*0.032*	*0.000*	[0.907 ; 1.033]	*623.71*
	d	***0.217***	***0.113***	***0.058***	**[-0.004 ; 0.438]**	

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 show no 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 were 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 both aggregate CO_2 emissions and each of its five 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 ($d = 1$). Furthermore, all data series exhibit long-term memory as all estimated parameters d lie within the interval (0, 0.5).

Total CO_2 emissions have a degree of persistence of d = 0.270. In relative terms, emission from gas flaring show the smallest degree of persistence, $d =$ 0.217, while emissions from coal consumption show the highest degree of persistence, $d =$ 0.471. Furthermore, the degree of persistence we estimate for aggregate emissions corresponds to the convex combination of the five individual results, which attests to the accuracy of our estimates.

With the exception of emissions from gas flaring combustion, all of the estimates of the fractional integration parameter are statistically significant at 1%. For aggregate emissions and emissions from solid fuels and from cement production, the upper bound is slightly greater than 0.5, leaving open the possibility that the different series may be non-stationary, though still mean reverting.

4.2 In-Sample Global CO_2 Emissions Forecasts

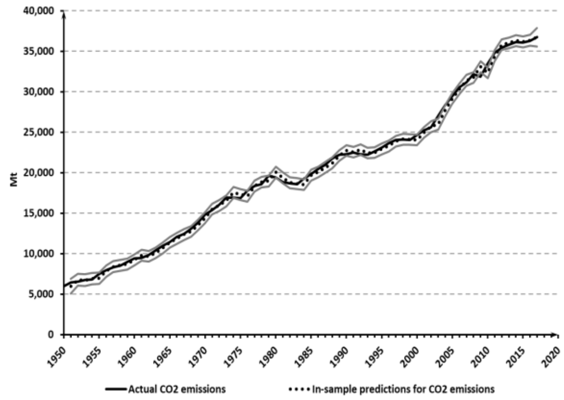
Figure 1 plots the actual values against the in-sample forecasts for global CO_2 emissions between 1950 and 2017. Table 3 summarizes our in-sample forecasting accuracy results.

We get excellent in-sample predictions with a MAPE ranging from a minimum of 3.2% for aggregate CO_2 emissions to a maximum of 6.8% for emissions from gas flaring. In addition, the percentage of projected values outside the confidence interval ranges from a minimum of 4.4% for total emissions to a maximum of 7.5% for emissions from gas flaring.

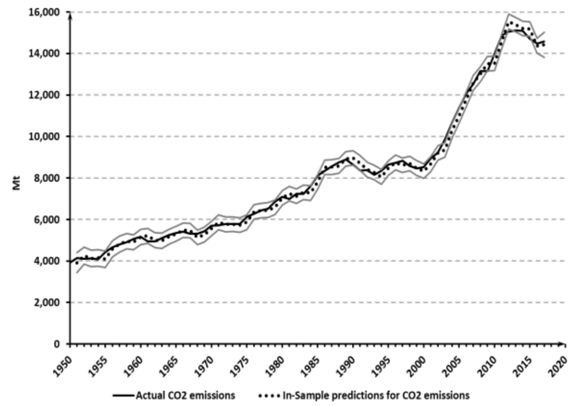
In turn, the U-statistic is very low, varying in a band between 0.01 and 0.05. This suggests that the predictions compare quite well with the observed values. Furthermore, the predictions are non-skewed and show a low variance, which suggests that they closely follow the changes in the observed values. In fact, more than 94% of the prediction error in all components under analysis is non-systematic.

Finally, the projections based on the aggregate results are very close to the sum of the projections for each of its five components. The difference is, on average, 1% for the in-sample projections discussed here and 4.5% for the out-of-sample projections presented below. This confirms the good performance of our ARFIMA approach.

a) Aggregate CO_2 Emissions



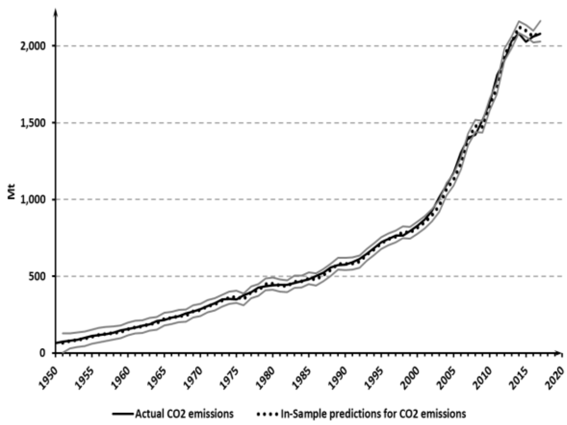
b) CO_2 Emissions from Solid Fuels



c) CO_2 Emissions from Liquid Fuels

d) CO_2 Emissions from Gas Fuels

e) CO_2 emissions from Cement Production



f) CO_2 Emissions from Gas Flaring

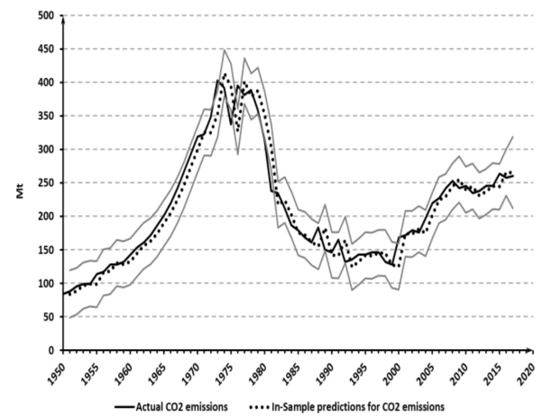


Figure 1. In-Sample CO_2 Predictions: 1950-2017

Table 3. In-Sample Forecasts Accuracy Analysis: 1950-2017

	CO_2 Emissions					
	Aggregate	Solid Fuels	Liquid Fuels	Gas Fuels	Cement	Gas Flaring
Mean Absolute % Error (MAPE)	3.2%	3.6%	4.2%	3.7%	3.9%	6.8%
Adj. Mean Absolute % Error (AMAPE)	2.3%	2.5%	2.9%	2.6%	2.7%	3.4%
Theil Inequality Coefficient	0.02	0.03	0.02	0.01	0.01	0.05
Mean Squared Error decomposition:						
Bias proportion	2.0%	0.1%	1.0%	1.4%	2.6%	2.5%
Variance proportion	0.8%	0.0%	1.6%	4.6%	0.2%	0.9%
Covariance proportion	97.2%	99.8%	97.5%	94.1%	97.2%	96.6%

5. ARFIMA CO_2 Emissions Forecasts and their Implications

5.1 The ARFIMA Forecasts 2018 - 2050

Having established a good in-sample forecasting performance for the ARFIMA estimates, we use these estimates to forecast CO_2 emissions until 2050. We present the results in Figure 2 while in Table 4 we present summary results relative to 2020 reference levels (the detailed results will be provided upon request to the authors).

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

From a disaggregated perspective, we forecast CO_2 emissions from liquid fuels, gas fuels, and cement production to be systematically above the 2010 reference levels. In turn, we project emissions from solid fuels and from gas flaring to be below the 2010 reference levels after the first few years into the forecasting horizon.

We forecast CO_2 emissions from liquid fuels to be 14.2% and 15.2% above the 2010 emissions levels by 2030 and 2050, respectively. In turn, the projected emissions from gas fuels are 29.9% and 42.2% above the 2010 level by 2030 and 2050, respectively. The same is true for the projected emissions from cement production, which will reach levels 33.0% and 27.4% above the 2010 levels by 2030 and 2050, respectively.

Conversely, projections of CO_2 emissions from solid fuels follow a decreasing pattern from 2021 onwards. By 2030 and 2050, the projected emissions are 12.9% and 24.3% below the 2010 level. In turn, the projected emissions from gas flaring start declining after 2026 and will reach levels 5.8% and 28.7% below the 2010 levels by 2030 and 2050, respectively.

5.2 The ARFIMA Forecasts and the IPCC Special Report 2018 Targets

Table 5 shows the policy efforts required to meet the new IPCC targets as implied by our ARFIMA forecasts. Figure 3 provides a depiction of the two relevant trajectories: the IPCC targets and the ARFIMA forecasts.

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 40.1% of 2010 levels, between 2030 and 2050. Accordingly, the total target accumulated reduction by 2050 corresponds to a reduction of 85.1% in emissions relative to 2010 levels.

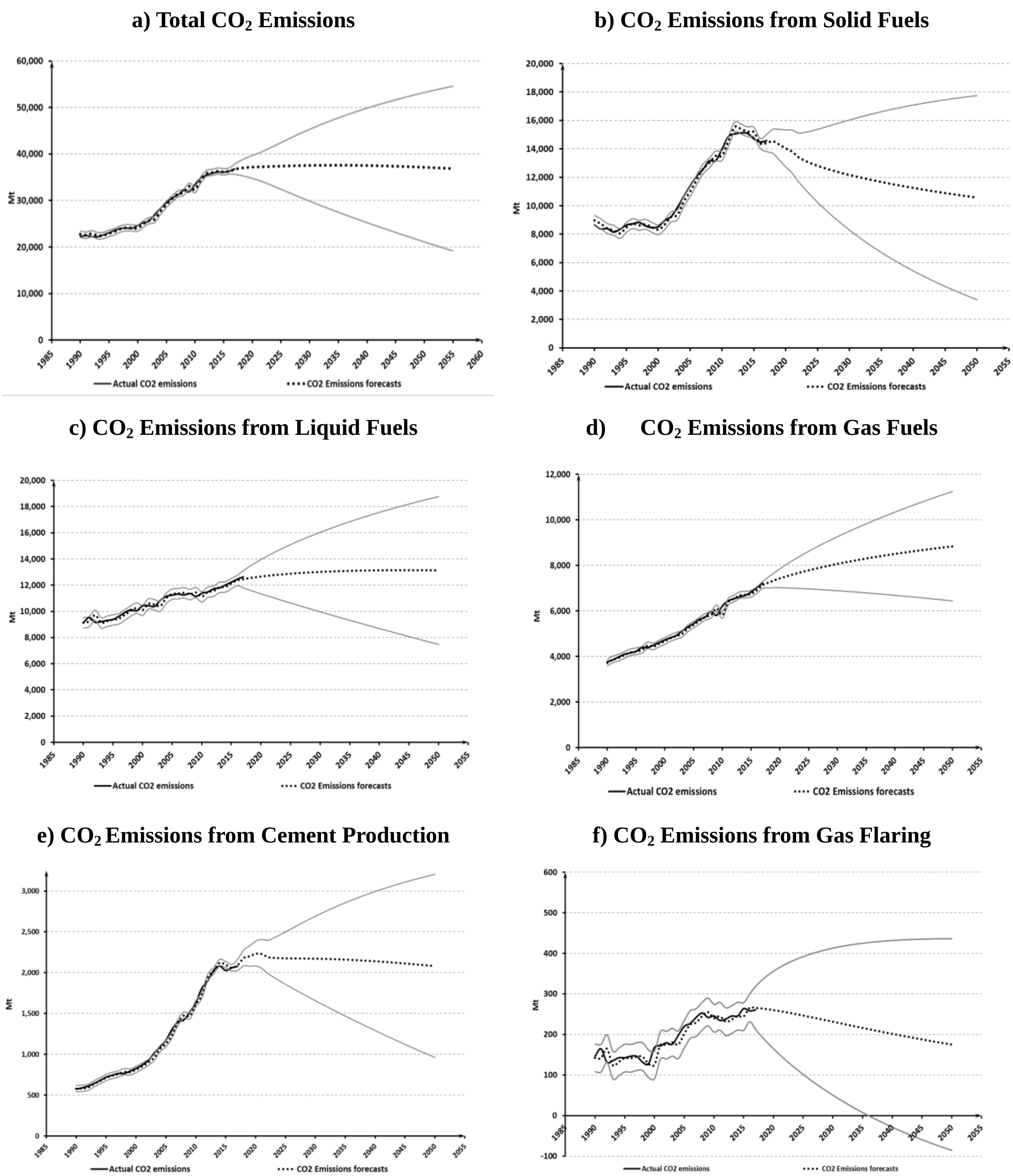


Figure 2. CO_2 Emissions Forecasts for 2018 – 2050

Table 4. CO_2 Emissions Forecasts Emissions Relative to 2010 Reference Levels (%)

	Aggregate	Solid Fuels	Liquid Fuels	Gas Fuels	Cement	Gas Flaring
2020	11.3	0.5	11.1	19.6	36.6	6.0
2030	12.4	-12.9	14.2	29.9	33.0	-5.8
2040	12.3	-19.4	15.3	36.9	31.1	-17.9
2050	11.1	-24.3	15.2	42.2	27.4	-28.7

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

	2030	2050
IPCC (2018) targets	**-45.0**	**-85.1**
Policy effort based on ARFIMA forecasts		
Total	-57.4	-97.4
Solid Fuels	-32.1	-72.0
Liquid Fuels	-59.2	-99.3
Gas Fuels	-74.9	-114.9
Cement Production	-78.0	-118.3
Gas Flaring	-39.2	-80.1

Of the greatest importance is the comparison of the IPCC policy CO_2 emissions targets with our ARFIMA reference scenario emissions. Since our forecasts capture the statistical information included in the sample, these forecasts provide the most fundamental reference case forecasts. We use these to assess the net policy effort, compatible with the carbon neutrality in 2050.

In order to meet the IPCC target for 2030 a policy effort is necessary that cuts 57.4% emissions relative to 2010 levels. From these, 12.4% corresponds to the extra effort due to the inertia of the natural CO_2 emissions system. In turn, for the 2050 target to be reached an additional effort of 97.4% of 2010 emissions is required. Therefore, the policy efforts for decarbonization are not just very large. They are also larger than implied by the IPCC targets. They are also frontloaded and in a way that clearly exceeds the frontloading already contemplated in the IPCC targets.

The general pattern described above where the inertia of the emission system increases the policy effort required to achieve IPCC targets also applies to emissions from liquid fuels, gas fuels, and from cement production. The policy efforts to achieve decarbonization by 2050 are 118.3% of 2010 levels for emissions from cement production, 114.9% for emissions from gas fuels, and 99.3% for liquid fuels.

On the other hand, the emissions from solid fuels and flaring gas combustion have a decreasing trend and, therefore, the inertia of the emissions system suggests that the policy efforts needed to promote the decarbonization of the economy by 2050 are lower than the IPCC goals themselves. In order to achieve the 2050 target, the policy effort for solid fuel emissions is 72% of the 2010 levels while for gas flaring it is 80.1%.

6. Summary, Conclusions, and Policy Implications

This work uses an ARFIMA approach to evaluate the degree of persistence of worldwide CO_2 emissions from solid, liquid, and gas fossil fuel combustion as well as gas flaring and cement production, and to make the corresponding forecasts into 2050. These forecasts, in turn, allow us to assess the policy effort required to meet the IPCC targets.

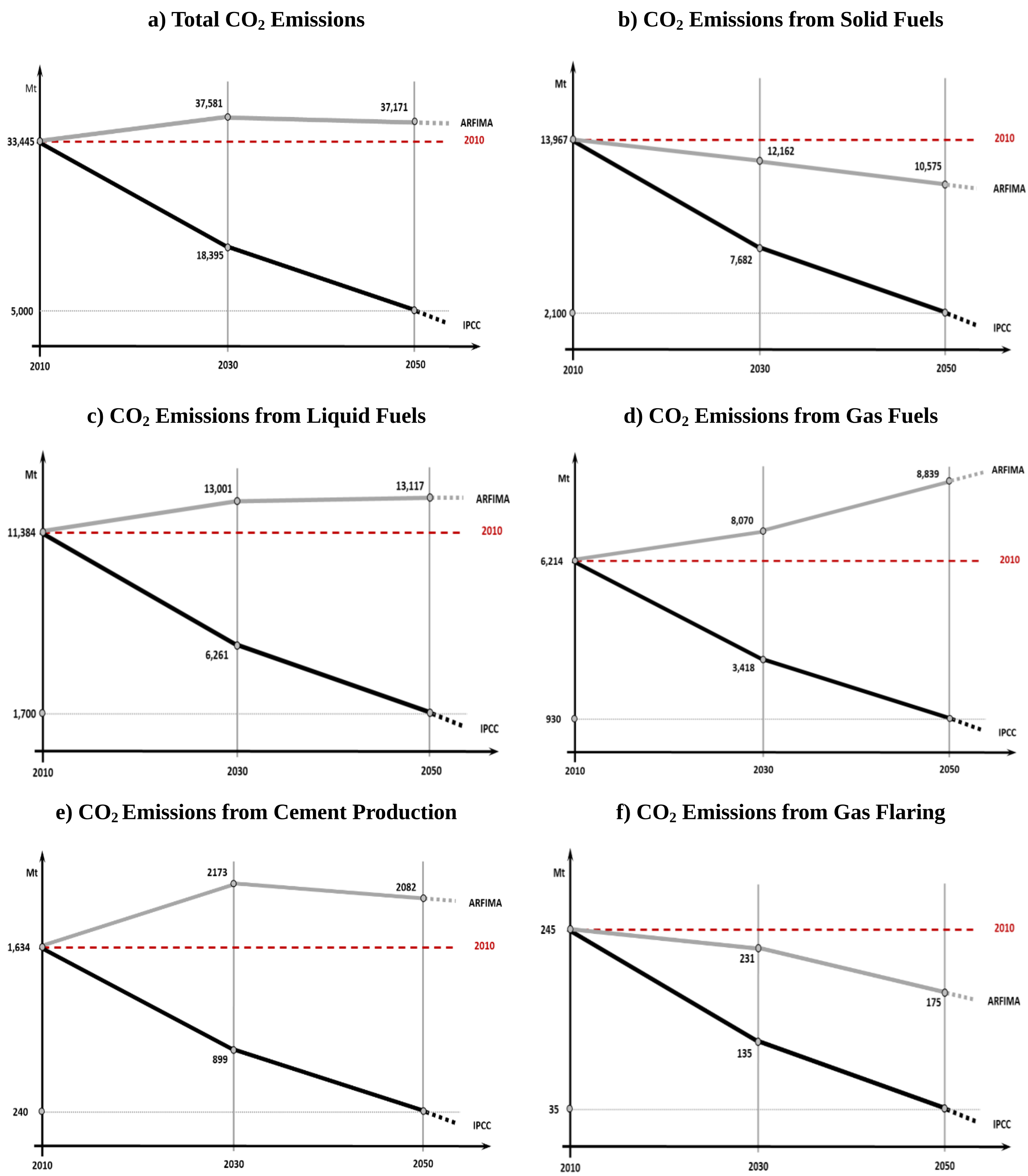


Figure 3. CO_2 Emissions: ARFIMA Projections versus IPCC Goals

Our empirical results suggest that CO_2 emissions, both at the aggregate level and for each of its five different components, are fractionally integrated processes. Accordingly, they show long-memory and the effects of shocks tend to dissipate at a slow hyperbolic rate. Emissions from liquid fuels and gas flaring exhibit the weakest degree of long-range dependence while emissions from solid fuels and cement have the strongest.

The long-memory nature of CO_2 emissions implies that any policy shock will have temporary effects albeit longer lasting than suggested in a traditional analysis of stationarity. The mean reversal property, 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.

According to our projections, worldwide CO_2 emissions will peak in 2034 and will slowly decline thereafter. Emissions in 2050 will be 11.1% above the 2010 levels. This aggregate pattern is due to the evolution of emissions from liquid fuels and gas. For emissions from combustion of solid fossil fuels, gas flaring, and cement production, we project eventually declining trajectories.

We measure the policy efforts required to decarbonize the world economy as the difference between the reductions of CO_2 emissions required to achieve the nominal IPCC targets and the evolution of emissions as measured by the underling ARFIMA projections. Our results suggest that at the aggregate level, to achieve such policy targets additional deliberate policy efforts are necessary leading to reduction in emissions by 57.4% and of 97.4% of the 2010 levels by 2030 and 2050, respectively. Accordingly, the necessary policy efforts are very sizeable and more so than suggested by the IPCC targets themselves.

At a disaggregated level, our results also suggest that emissions from liquid fuels, gas fuels and cement production will reach levels clearly above the IPCC 2010 reference value. Accordingly, the inertia underlying the natural emissions system will require policy efforts equivalent to 118.3%, 114.9% and 99.3% of 2010 emissions, respectively, in order to achieve the 2050 target. By contrast, for emissions from solid fuels and flaring gas, inertia will reduce the policy effort required by 72.0% and 80.1% of 2010 levels, respectively.

The policy efforts necessary to reach carbon neutrality by 2050 are not only sizeable. They are also frontloaded. Indeed, about 60% of the necessary reductions have to be achieved in the next decade and just 40% over the next two decades. By contrast, the IPCC targets considered in isolation would seem to imply a share of efforts of about 52.9% over the next decade. The policy efforts for reduction in emissions from liquid fuels are at about the aggregate patterns. In turn, policy efforts for gas fuels and cement production are more frontloaded than indicated by aggregate emissions while those from solid fuel and gas flaring are much less frontloaded.

Finally, 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 components of total CO2 emissions – both in terms of their magnitude and their trajectory. Given the differences in the inertia of the different types of emissions a one-size fits all approach is not appropriate.

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.

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