Gabinete de Estratégia e Estudos

GEE Paper

126

Agosto de 2019

Reference Forecasts for CO2 Emissions from Fossil-Fuel Combustion and Cement Production in Portugal

José M. Belbute| Alfredo M. Pereira

Gabinete de Estratégia e Estudos do Ministério da Economia
Office for Strategy and Studies of the Ministry of Economy
Rua da Prata, n.º 8 – 1149-057 Lisboa – Portugal
www.gee.gov.pt
ISSN (online): 1647-6212

Reference Forecasts for CO2 Emissions from Fossil-Fuel Combustion and Cement Production in Portugal

José M. Belbute [1], Alfredo M. Pereira [2]

Abstract

We provide reference forecasts for CO2 emissions from burning fuel fossil and cement production in Portugal based on an ARFIMA model approach and using annual data from 1950 to 2017. Our "business as usual" projections suggest a pattern of decarbonization that will cause the reduction of 3.3 Mt until 2030 and 5.1 Mt between 2030 and 2050. This scenario allows us to assess effort required by the new IPCC goals to ensure carbon neutrality by 2050. For this objective to be achieved it is necessary for emissions to be reduced by 39.6 Mt by 2050. Our results suggest that of these, only 8.4 Mt will result from the inertia of the national emissions system. The remaining reduction on emissions of 31.2 Mt of CO2 will require additional policy efforts. Accordingly, our results suggest that about 79% of the reductions necessary to achieve IPCC goals require deliberate policy efforts. Finally, the presence in the data of long memory with mean reversion suggests that policies must be persistent to ensure that these reductions in emissions are also permanent.

JEL Classification: C22, C53, O52, Q54.

Keywords: CO2 emissions, IPCC emission targets, long memory, ARFIMA, Portugal

Acknowledgments

The first author would like to acknowledge financial support from FCT–Fundação para a Ciência e a Tecnologia (grant UID/ECO/04007/2019).

Note: This article is sole responsibility of the authors and do not necessarily reflect the positions of GEE or the Portuguese Ministry of Economy.

[1] Department of Economics, University of Évora, Portugal. Center for Advanced Studies in Management and Economics – CEFAGE, Portugal. Email: jbelbute@uevora.pt

[2] Department of Economics, William and Mary, Williamsburg, VA 23187, USA. Email: ampere@wm.edu

1. Introduction

The purpose of this article is to provide reference forecasts for CO2 emissions in Portugal based on an ARFIMA approach. We consider both aggregate emissions and each of its main sources – solid fuels, liquid fuels, gas, and cement production. Our ultimate objective is to compare our reference forecasts with the relevant emissions targets and thereby ascertain how much of an additional policy effort is 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, for example, IPCC (2014)].

In the last three decades, Portugal has implemented policies aligned with the international guidelines and policy targets for climate change, namely the European Union climate change strategy, the Kyoto Protocol and more recently the Paris Agreement. [See, for example, the Strategic Framework for Climate Policy, QEPiC 2030 (2015), the Roadmap for Carbon Neutrality, RNC2050 (2018), and the National Plan for Energy and Climate, PNEC2030 (2019)]. As a result, we have observed the introduction of natural gas, the strategic option in favor of renewable energy sources, the stimulus towards energy efficiency, the improvement of the land use, land-use change and forestry sectors, and the participation in the European Trading System. Considered together, these policy efforts have contributed both to the successful completion of the first Kyoto Protocol's period of compliance objectives and the reduction in emissions observed since 2002.

Recently, the IPCC's 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. Moreover, global net anthropogenic emissions of CO2 would need to fall by about 45% from 2010 levels by 2030, reaching 'net zero' around 2050. These new targets were incorporated into the Roadmap for Carbon Neutrality, RNC2050 (2018) released by the Portuguese government in December 2018.

Identifying the proper reference scenario is a critical first step in ascertaining the extent of the policy efforts required to achieve any policy target for emissions, and thereby determining the costs involved in achieving such goals. Hence, there are two key policy questions in these matters in Portugal. The first question deals with identifying what will emissions in 2030 and 2050 be under a business as usual reference scenario. The second question, and as a corollary, is the determination of the dimension of the additional policy efforts needed to accomplish such emission targets.

Specifying a reference scenario, as 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 CO2 emissions in Portugal based on a comprehensive statistical analysis of the different time series and recognizing the possible presence of long-memory through fractional integration. Accordingly, our forecasts rely strictly 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 emissions forecast. See Belbute and Pereira (2015) for an application of this forecasting methodology to develop reference scenarios for world CO2 emissions.

There is now an extensive literature on fractional integration, which goes well 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) and Gil-Alana et al. (2015) and Belbute and Pereira (2016, and 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.

The fractional integration approach goes beyond the stationary/non-stationary dichotomy to consider the possibility that variables may follow a long memory process. 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 that there is significant dependence between observations widely separated in time, and, therefore, the effects of policy shocks are temporary but long lasting. Accordingly, the fractional integration properties of CO2 emissions have important policy implications for the specification of long-term reference case scenarios for emissions.

The remainder of this paper is organized as follows. Section 2 presents 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 other available reference forecasts and national policy scenarios. 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 CO2 emissions in Portugal for the period between 1950 and 2017. The data until 2014 is from the Carbon-Dioxide Information Analysis Centre [see Le Quére et al. (2015) and Boden et. al. (2017)]. This data set contains information going back to 1870. Nevertheless, given the profound structural changes that occurred after World War II, we only use data starting in 1950. Emissions between 2015 and 2017 were obtained using the values reported in the National Inventory of GHG Emissions, PNIRGHG (2018), and the Roadmap for Carbon Neutrality, RNC 2050 (2018).

Aggregate CO2 emissions in Portugal are the sum of four components: CO2 emissions from burning fossil fuels – solid/coal, liquid/oil, and gas, and CO2 emissions from cement production. There are no CO2 emissions from gas flaring. Moreover, we 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. It includes information about total CO2 emissions in the first year of each decade as well as the mean shares per decade of emissions from combustion of solid, liquid, and gas fossil fuels and from cement production in the total emissions.

Table 1 – Portugal CO_2 Emissions from Fossil Fuel Combustion and Cement Production

Aggregate CO2 emissions		Average Shares of Total Emissions (%)				
Years	**Mt**	**Years**	**Solid Fuels**	**Liquid Fuels**	**Gas Fuels**	**Cement Production**
1950	5.621	**1950-1959**	37.0	56.7	-	6.3
1960	8.218	**1960-1969**	26.2	66.6	-	7.2
1970	15.246	**1970-1979**	9.6	81.8	-	8.6
1980	26.963	**1980-1989**	12.4	78.1	-	9.5
1990	42.286	**1990-1999**	24.5	66.3	3.3	8.2
2000	62.680	**2000-2009**	19.9	60.6	12.3	7.2
2010	48.097	**2010-2017**	20.9	54.9	18.9	5.3
2017	50.784	**2017**	22.5	55.1	17	5.5
1950-2017		**1950-2017**	18.4	62.4	12.7	7.1

In the second half of the 20th Century, total CO2 emissions grew at a steady pace. This trend was reverted in the last two decades with emissions decreasing progressively until the end of the sample period. The annual flow of CO2 emissions peaked in 2002 at 66.7 Mt. By 2017, emissions reached 50.8 Mt, a figure 20% and 5.6% above the 1990 and 2010 reference levels, respectively. For perspective, Portugal's total CO2 emissions in 2017 represent about 1.4% of total European Union emissions and just 0.13% of worldwide emissions.

CO2 emissions from solid fossil fuel combustion represented on average over the sample period a little more than 18.6% of total emissions. These emissions reached their lowest point in relative terms in the 1970s and have shown a relatively steady increase ever since. In the last few years of the sample, they represented 22.7% of total emissions.

The combustion of liquid fuels was the dominant source of CO_2 emissions during the sample period, contributing on average to around 61.4% of total emissions. In the 1970s and 80s these emissions represented close to 80% of emissions, a number that has significantly declined ever since. By the last years of the sample, they amounted to 54.9% of emissions.

Natural gas has developed rapidly after its introduction in 1998. Accordingly, related CO_2 emissions has increased significantly. The average share from gas in aggregate emissions for the period 1998–2017 was 12.7%, a share that has been steadily increasing over the last three decades to reach 17% over the last years of the sample.

Finally, CO_2 emissions from cement production account for 7.1% of total emissions over the sample period. These emissions peaked in the 1970s, 80s, and 90s. Their relative share of emissions decreased in the last two decades to reach just 5.3% in the most recent years of the sample.

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

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

where, β is the coefficients vector, z_t represents all deterministic factors of the process, y_t, and $t = 1, 2, \dots n$, 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 and Joyeux (1980), Granger (1980, 1981), Sowell (1992a, 1992b), Baillie (1996), Palma (2007) and Hassler et all (2016), Belbute and Pereira (2016)].

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 $\mathrm{AR(p)}$ and $\mathrm{MA(q)}$ terms are a 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 $\{\mathrm{u_t}\}$ in (1) is an $\mathrm{ARMA(p,q)}$, then the process $\{\mathrm{x_t}\}$ is an $\mathrm{ARFIMA(p,d,q)}$ 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 $\mathrm{e_t}$ as white noise. Clearly, the process is stationary and invertible for $-0.5 < \mathrm{d} < 0.5$.

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

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

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

3.3 ARFIMA Forecasting and Prediction-Accuracy Assessment

Given the symmetry properties of the covariance matrix, Vcan be factored as $\mathrm{V} = \mathrm{LDL'}$, where $\mathrm{D} = \mathrm{Diag(v_t)}$ and 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 $\tau_t = \mathrm{V_t^{-1}}\gamma_t$, $\gamma_t = (\gamma_1,\ \gamma_2, \dots ,\ \gamma_t)'$ and $\mathrm{V_t}$ is the $\mathrm{t} \times \mathrm{t}$ upper left sub-matrix of 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

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

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

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. 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 Theil inequality coefficient, as provided by the U-statistic, yields a measure of how well estimated values compares to a corresponding time series of observed values. It 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. Naturally, the three components add up to one.

4. The Basic Empirical Results

4.1 Fractional Integration Analysis

Table 2 presents 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.

Preliminary Lee and Strazicich (2003) tests for structural changes point to possible structural break points around 2002 for total emissions, emissions from liquid fuels and cement production, and around 1998 for coal. When included in the ARFIMA models, however, the corresponding dummy coefficients are not statistically significant. Furthermore, the best specification of the ARFIMA models as indicated by the BIC does not include structural breaks. For this reason, the empirical results in this paper do not consider structural breaks. In fact and naturally given this evidence, results with structural breaks do not differ in any meaningful way from those presented here.

Table 2 – Fractional-Integration Results: 1950-2017

Variable	**Coefficient**	**Estimates**	**Std. Err. (*p-value*)**	***Confidence Intervals***	**BIC**
Aggregate CO2 emissions	***d***	**0.447**	**0.079 (*0.000*)**	**[0.293 ; 0.601]**	331.742
	ϕ_1	0.602	0.138 (*0.000*)	[0.331 ; 0.873]	
	ϕ_3	0.339	0.120 (*0.005*)	[0.102 ; 0.575]	
CO2 emissions from solid fuels	***d***	**0.440**	**0.086 (0.000)**	**[0.272 ; 0.608]**	216.876
	ϕ_1	0.479	0.135 (*0.000*)	[0.215 ; 0.743]	
	ϕ_3	0.388	*0.103 (0.000)*	[0.187 ; 0.590]	
CO2 emissions from liquid fuels	***d***	**0.469**	**0.044 (*0.000*)**	**[0.383 ; 0.555]**	286.220
	ϕ_1	0.532	0.099 (*0.000*)	[0.337 ; 0.727]	
	ϕ_3	0.393	*0.093 (0.000)*	[0.210 ; 0.576]	
Co2 emissions from gas fuels	***d***	**0.267**	**0.172 *(0.121)***	**[-0.071 ; 0.605]**	69.562
	ϕ_1	0.951	0.059 *(0.000)*	[0.835 ; 1.067]	
CO2 emissions from cement production	***d***	**0.479**	**0.031 (*0.000*)**	**[0.419 ; 0.540]**	120.731
	ϕ_1	0.497	0.126 (*0.000*)	[0.250 ; 0.744]	

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.

Overall, our results provide strong empirical evidence for the non-rejection of the presence of long memory for both aggregate CO2 emissions as well as its different 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 = 0.447, which literally corresponds to the convex combination of the persistent levels estimated for each of its four individual components. In relative terms, emission from gas show the smallest degree of persistence, d= 0.267, while emissions form cement production show the highest degree of persistence, d= 0.478.

With the exception of CO2 emissions from gas combustion, all of the estimates of the fractional integration parameter are statistically significant at 1%. The lower precision of the estimate for emissions from gas is due to the smaller sample size for this variable.

Finally, the confidence intervals for the estimated fractional integration parameters are relatively narrow and always in the positive range. In all cases, however, the upper bound is slightly greater than 0.5, leaving open the marginal possibility that the different series may be non-stationary, though still would be mean reverting.

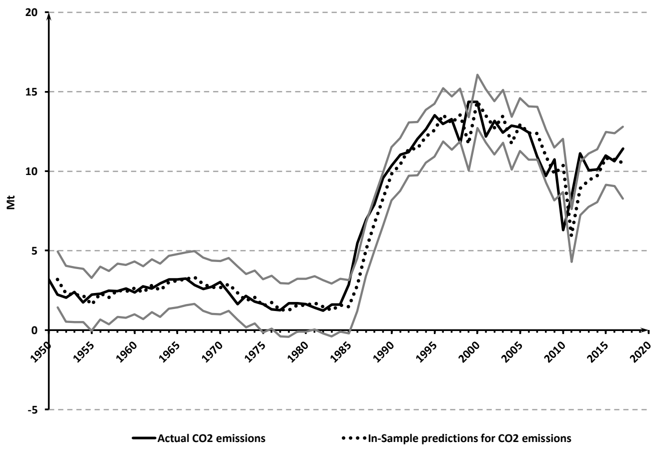
4.2 In-Sample Global CO2 Emissions Forecasts

Figure 1 plots the actual values against the in-sample forecasts for global CO2 emissions between 1950 and 2017. Table 3 summarizes our forecasting accuracy analysis for the in-sample predictions.

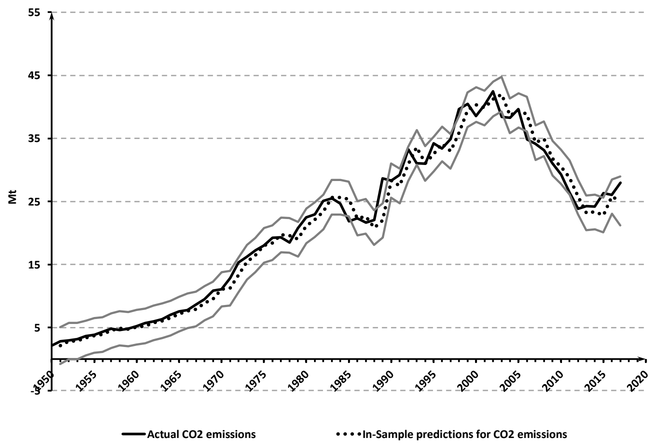
Figure 1 - In-sample CO2 Predictions: 1950-2017

a) Aggregate CO2 emissions

b) CO2 emissions from solid fuels

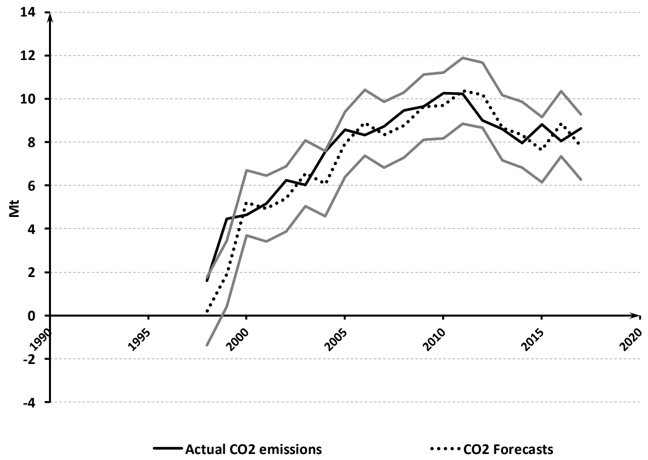


c) CO2 emissions from liquid fuels



d) CO2 emissions from gas fuels

e) CO2 emissions from cement production



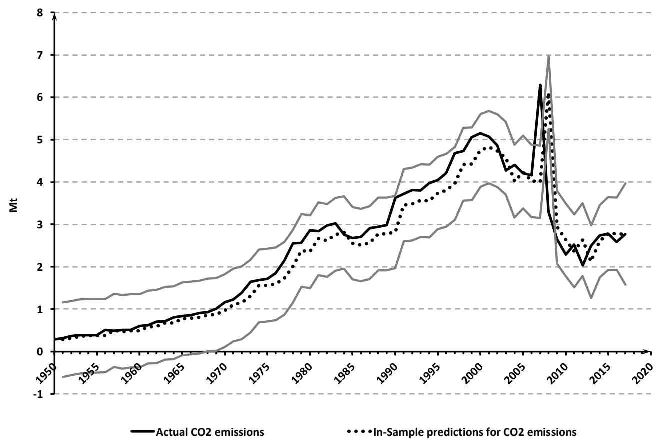


Table 3 - In-Sample Forecasts Accuracy Analysis: 1950-2017

	CO2 Emissions				
	Aggregate CO2	**Solid Fuel**	**Liquid Fuel**	**Gas Fuel**	**Cement production**
Mean Absolute Percentage Error (MAPE)	6.1%	14.7%	7.3%	8.0%	12.8%
Adjusted Mean Absolute Percentage Error (AMAPE)	3.9%	8.2%	4.5%	4.1%	7.3%
Theil Inequality Coefficient	0.03	0.07	0.03	0.05	0.09
Mean Squared Error decomposition:					
Bias proportion	4.9%	3.4%	3.2%	4.3%	8.7%
Variance proportion	1.5%	0.0%	2.3%	1.0%	1.2%
Covariance proportion	93.5%	96.5%	94.5%	94.8%	90.1%

In general, we get excellent in-sample predictions for both aggregate CO2 emissions and each one of its four components. The MAPE ranges from a minimum of 6.1% for total emissions to a maximum of 14.7% for emissions from coal. In addition, the percentage of projected values outside the confidence interval ranges from a minimum of 1.5% for emissions from cement production to a maximum of 7.4% for emissions from coal combustion.

In turn, the U-statistic shows a very small value, varying in a band between 0.03 and 0.09. This suggests that the predictions compare quite well with the observed values. Furthermore, the predictions are non-skewed and show a low variance. More than 90% of the prediction error in all components under analysis is non-systematic. The less precise results for natural gas emissions are, once again, due to its smaller sample size.

5. ARFIMA CO2 Emissions Forecasts and their Implications

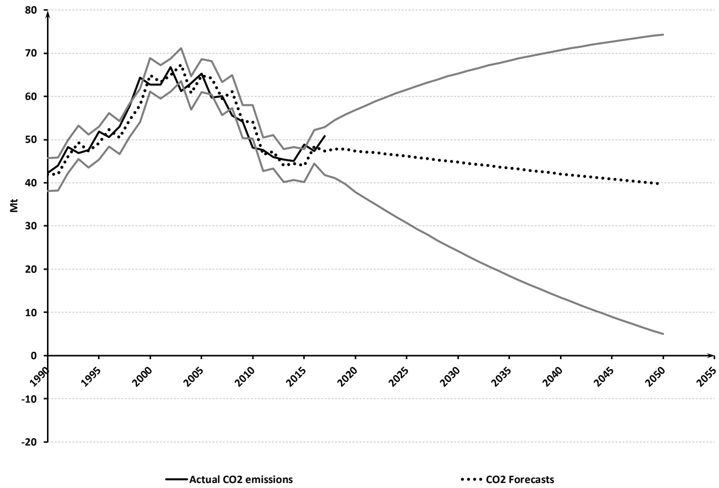
5.1 The ARFIMA Forecasts 2018 – 2050

Having established a good forecasting performance of the different ARFIMA models, we use these estimates to forecast CO2 emissions until 2050. The detailed results are presented in Figure 2 and Tables A1 to A5 in the Appendix. In turn, summary results relative to 2010 reference levels are presented in Table 4.

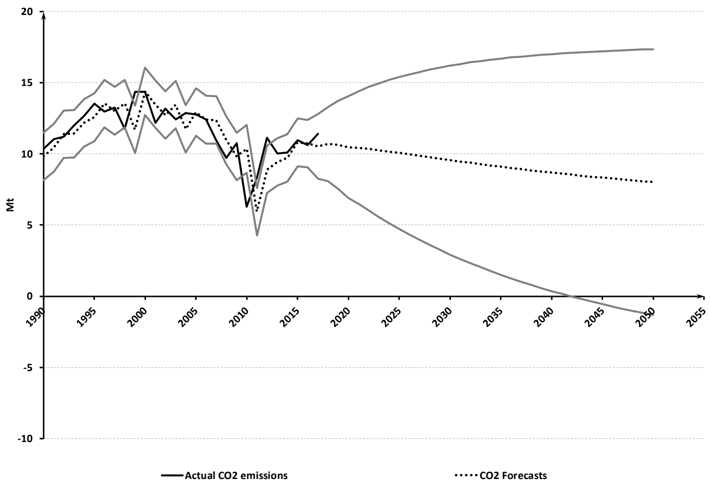
Total CO2 emissions are projected to decrease from 50.8 Mt in 2017 to 39.7 Mt in 2050. Emissions in 2030 and 2050 are forecasted to be about 6.9% and 17.4% below the 2010 reference level, respectively. Accordingly, the projected reductions in emissions are more pronounced until 2030 – an average annual reduction of about 0.46 Mt, and noticeably slower in the next two decades – an average annual reduction of 0.25 Mt.

Figure 2 – CO_2 emissions forecasts: 2018 - 2050

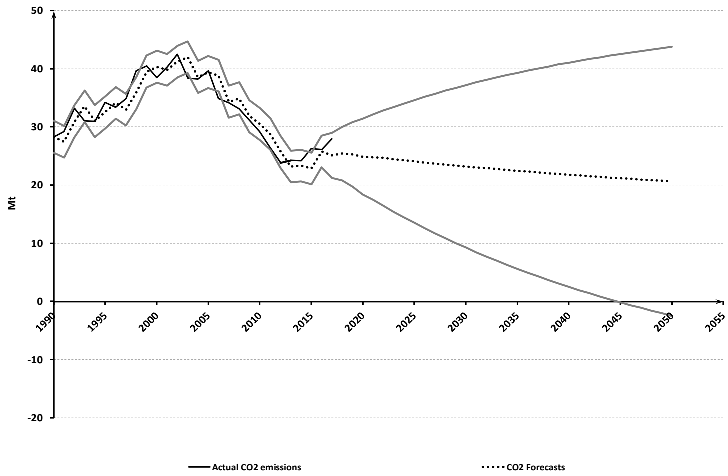
a) Total CO2 Emissions



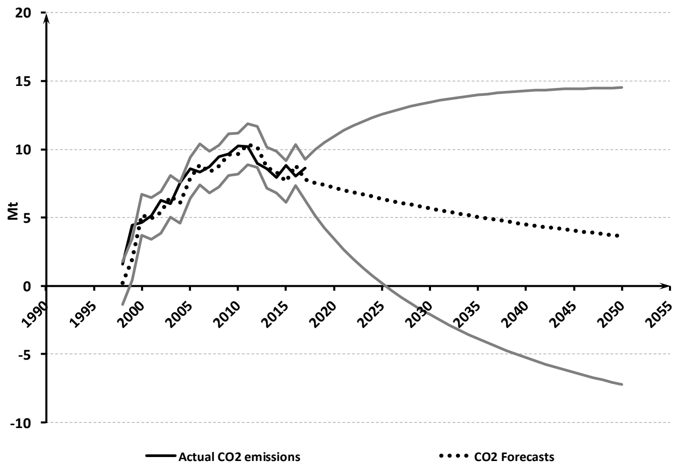
b) CO_2 Emissions from solid fuels



c) CO_2 Emissions from liquid fuels



d) CO_2 Emissions from gas fuels



e) CO_2 Emissions from cement production

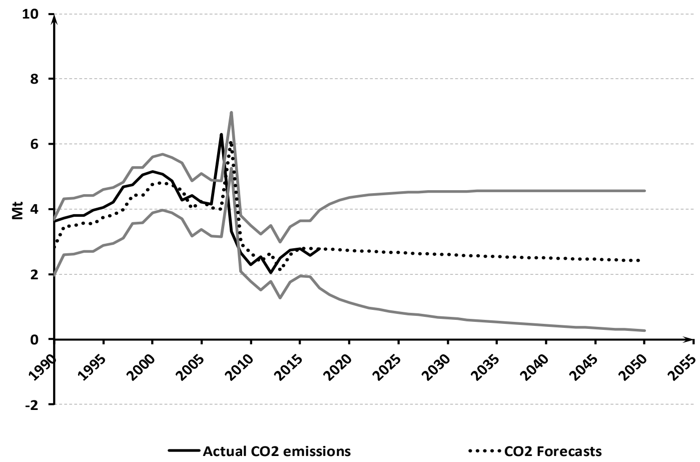


Table 4 – CO_2 Emissions Forecasts: Changes in Emissions Relative to 2010 Reference Levels (%)

	Aggregate CO_2	Solid fuel	Liquid fuel	Gas	Cement
2020	-1.7	66.3	-14.8	-29.9	19.4
2030	-6.9	51.9	-20.6	-44.7	13.5
2040	-12.5	38.0	-25.5	-56.0	9.0
2050	-17.5	27.3	-29.4	-64.4	5.7

This general pattern of reduction in total emissions, is also identified in its different components, although in different manners and to different extents. Noticeably, we project emissions for liquid fuel and gas fuel combustions to be always below the 2010 reference levels and emissions from solid fuel combustion and from cement production to be always above the 2010 reference levels. Emissions from the combustion of liquid fuels are projected decline by 2030 and 2050 to 20.6% and 29.4% below the 2010 level while the projected emissions from natural gas by 2030 and 2050 are 44.7% and 64.4% below the level in 2010, at a level of 3.7 Mt. In turn, projections of emissions from coal in 2030 and 2050 are 51.9% and 27.3% higher than the reference year while projected emissions from cement production will reach levels 13.5% and 5.7% above the 2010 levels by 2030 and 2050, respectively.

5.2 The ARFIMA Forecasts and the IPCC Special Report 2018 and RNC2050 Targets

Recently, the IPCC's 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 which will require a fall by about 45% from 2010 emission levels by 2030 and reaching 'net zero' around 2050.

The IPCC emissions targets were applied and adopted in general terms to the Portuguese case in the Roadmap for Carbon Neutrality – RNC2050 (2018), which establishes the strategic framework of public policies in Portugal aiming at carbon neutrality in 2050. The RNC2050 does not set specific targets for 2030 and 2050, but rather provides confidence intervals based on three alternative scenarios. However, it is reasonable to assume that the RNC2050 points to an average reduction of 40% of emissions by 2030 and of 82.3% by 2050, with reference to 2010 emissions. As a result, the RNC2050 projects a level of emissions by 2050 in line with IPCC 2018 guidelines, although by 2030 the projected reduction is slightly lower than the IPCC guidelines.

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

	2030	2050	
		Increment over 2030	Total
Policy targets			
(1) IPCC new targets (2018)	-45.0%	-37.3%	-82.3%
(2) RNC2050	-40.0%	-42.3%	-82.3%
Reference scenarios			
(3) ARFIMA model	-6.9%	-10.6%	-17.5%
Additional policy efforts			
(4) Under IPCC new targets	-38.0%	-26.9%	-64.9%
(5) RNC2050	-33.1%	-31.8%	-64.9%

The IPCC and the RNC2050 policy targets are presented in lines 1 and 2 of Table 5. Under the IPCC targets, CO2 emissions in Portugal would have to decrease by 21.6 Mt or 45% of 2010 emissions by 2030 and a further 18.0Mt, or a further 37.3% of 2010 levels, between 2030 and 2050. The total target accumulated reduction by 2050 is 39.6Mt, which corresponds to a reduction of 82.3% relative to 2010. By construction, the objectives of the RNC2050 for 2050 are the same as the IPCC. The projected trajectory of decrease in emissions under the RNC2050 is slightly less frontloaded with a projected decrease of 40.0% in 2030 relative to 2010 values.

Of the greatest importance is the comparison of these policy targets with our reference scenario. Line 3 of Table 5 indicates that the inertia effect estimated according to the ARFIMA model projections is responsible for the reduction of 6.9% of emissions by 2030 and of 10.5% between this year and 2050, with a total cumulative reduction of 17.4%. This implies that the inertia of the Portuguese emissions system is very far from sufficient to generate the path of CO2 emissions necessary to achieve the IPCC targets towards carbon neutrality by 2050.

Since our CO2 emissions forecasts provide the most fundamental reference case forecast of emissions, they can be used to assess the net policy effort necessary to achieve emissions goals. This information is provided in lines 4 and 5 of Table 5 and represents the difference between the IPCC and the RNC2050 policy targets and the ARFIMA model forecasts, respectively.

Line 4 of Table 5 indicates that a policy effort that cuts 38.1% of the 45% needed to meet the IPCC mid-term target in 2030 will be necessary. The remaining 6.9% are achieved through the inertia of the emissions system. By 2050, maintaining a policy agenda consistent with the overall objective of an 82.3% reduction in emissions will require an additional policy effort of 47.4% while inertia will be responsible for reducing 17.5% of emissions this year. Accordingly, the inertia of the system will lead to just 15% of the total target reduction in emissions necessary by 2030 and 27% of the reductions necessary by 2050. The remaining efforts have to come from deliberate decarbonization policies.

Finally, it should also be noted that the new IPCC guidelines impose a more stringent policy effort until 2030 - a 3.5% average annual reduction in emissions than the subsequent 20 years – a 1.4% average annual reduction in emissions. The opposite is true under the RNC2050. This is a straightforward implications of different 2030 targets coupled with the same 2050 target in the two cases.

6. Summary, Conclusions, and Policy Implications

This work uses an ARFIMA approach to evaluate the degree of persistence of total CO2 emissions from fossil fuel combustion – coal, oil, and gas - and cement production in Portugal, and to make projections of CO2 emissions until 2050. These ARFIMA projections allow us to assess the policy effort required by the Portuguese authorities to enable the country to meet the new IPCC and RNC2050 targets and thereby contribute to the global effort to limit the average global average temperature rise to 1.5 ° C.

Our empirical results suggest that CO2 emissions both at the aggregate level and for each of its four different components are fractionally integrated processes. Accordingly, they show long-memory and the effects of shocks tend to dissipate at a slow hyperbolic rate. Moreover, the degree of fractional integration does not significantly differ among all variables and the degree of fractional integration for aggregate CO2 emissions is very close to the convex combination of the degrees of fractional integration for the four emission sources considered.

In terms of projections for the CO2 emissions, our approach uses only the information included in the stochastic process underlying the baseline data, in a context in which the existing policies in 2017 remain invariant. Our projections for CO2 emissions suggest an inertial pattern of decarbonisation of the economy, which translates into emissions reductions of respectively 6.9% and 17.5% in 2030 and 2050 relative to 2010 levels.

The policy effort required to reach carbon neutrality in 2050 is measured by the difference between the reduction of emissions required by the IPCC 2018 and RNC2050 targets and the ARFIMA emissions projections. Our results suggest that to achieve such policy targets by 2050, additional policy efforts are necessary leading to a reduction in emissions of 64.9% of the 2010 levels. The required long-term policy effort is the same for the IPCC2018 and RNC2050 since both have the same objective for emissions in 2050. The IPCC2018 targets, however, require a larger additional policy effort by 2030 and, consequently, lower additional policy effort in the subsequent 20 years compared to the RNC2050 targets. That is, IPCC2018 targets lead to the need of frontloaded policies.

These results have important policy implications. First, our emissions projections capture the inertia effect underlying CO2 emissions and this exercise allows us to assess the policy effort involved in the intermediate and final targets. The results clearly suggest that the underlying inertia of the reference scenario is insufficient to generate a path of CO2 emissions that would generally achieve carbon neutrality by 2050 and in particular the intermediate IPCC targets. This implies that deliberate additional policy efforts are crucial in attaining the desirable emission targets.

Second, 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 national strategy for achieving carbon neutrality in 2050 where it will be crucial to promote permanent changes in behavior and not just short term fixes.

Finally, the policy efforts required to achieve decarbonization – a reduction in emissions by 2050 equivalent to 65% of the 2010 reference levels - are very demanding and frontloaded under the IPCC2018 targets. The magnitude and urgency of these efforts, however, does not seem to be not matched by the consideration of any significant actions in the current policy debate. This is true even if we take into account the scheduled closure of the two coal-fueled thermoelectric plants still in operation in the country, which are responsible for about 14% of total CO2 emissions.

7. References

Apergis, N. and C. Tsoumas (2012). "Long Memory and Disaggregated Energy Consumption: Evidence from Fossil Fuels, Coal and Electricity Retail in the US," **Energy Economics** 34, 1082-87.

Apergis, N. and C. Tsoumas (2011). "Integration Properties of Disaggregated Solar, Geothermal and Biomass Energy Consumption in the US," **Energy Policy** 39, 5474-79.

Baillie, R. (1996). "Long-Memory Processes and Fractional Integration in Econometrics," **Journal of Econometrics** 73, 5–59.

Barassi, M., M. Cole, and R. Elliott (2011). "The Stochastic Convergence of CO2Emissions: ALong Memory Approach," **Environmental Resource Economics** 49, 367-385.

Barros, C., L. Gil-Alana, and F. de Gracia (2016). "Stationarity and Long Range Dependence of Carbon Dioxide Emissions: Evidence for Disaggregated Data," **Environmental Resource Economics** 63, 45-56.

Belbute, J. and A. Pereira (2017). "Do Global CO2 Emissions from Fossil-Fuel Consumption Exhibit Long Memory? A Fractional Integration Analysis," **Applied Economics**, Forthcoming [DOI:10.1080/00036846.2016.1273508].

Belbute, J. and A. Pereira (2016). "Does Final Energy Demand in Portugal Exhibit Long Memory? A Fractional Integration Analysis," **The Portuguese Economic Journal**-15(2), 59-77.

Belbute, J. and A. Pereira (2015). "An Alternative Reference Scenario for Global CO2 Emissions from Fuel Consumption: An ARFIMA Approach," **Economics Letters** 135, 108-111.

Beran, J. (1994). "Statistics for Long-Memory process," Boca Raton, Chapman & Hall/CRC.

Boden, T.A., G. Marland, and R. J. Andres. (2017). "Global, Regional, and National Fossil-Fuel CO2 Emissions," Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., USA. DOI: 10.3334/CDIAC/00001_V2017.

Bollerslev, T. and O. Mikkelsen (1996). "Modeling and pricing long memory in stock market volatility," **Journal of Econometrics**, 73, 151-184.

Diebold, F.X. and G.D. Rudebusch (1991)."On the power of Dickey-Fuller tests against fractional alternatives," **Economics Letters** 35, 155-160.

Gil-Alana, L., J. Cunado, and R. Gupta (2015)."Persistence, Mean-Reversion, and Non-linearities in CO2 Emissions: The Cases of China, India, UK and US," University of Pretoria Department of Economics Working Paper Series2015-28.

Granger C.W.J. (1981). “Some Properties of Time Series Data and their Use in Econometric Model Specification,” **Journal of Econometrics** 16, 121-30.

Granger C.W.J. (1980). “Long Memory Relationships and the Aggregation of Dynamic Models,” **Journal of Econometrics** 14, 227-38.

Granger C.W.J. and R. Joyeux (1980). “An Introduction to Long Memory Time Series and Fractional Differencing,” **Journal of Time Series Analysis** 1, 15-29.

Hassler, U., P. Rodrigues and A. Rubia (2016). “Quantile Regression for Long Memory Testing: A Case of Realized Volatility,” **Journal of Financial Econometrics**, 14 (4), 693-724.

IPCC (2018). “Special Report on Global Warming of 1.5 °C (SR15),” Intergovernmental Panel on Climate Change annual Report, UNEP.

IPCC (2014), “Climate Change 2014: Synthesis Report,”**Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change** [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Lee, J. and M. Strazicich (2003),” Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks,” **The Review of Economics and Statistics**, 85 (4), 1082-1089.

Le Quére, C, R Moriarty, RM Andrew, JG Canadell, S Sitch, JI Korsbakken, P Friedlingstein, GP Peters, RJ Andres, TA Boden, RA Houghton, JI House, RF Keeling, P Tans, A Arneth, DCE Bakker, L Barbero, L Bopp, J Chang, F Chevallier, LP Chini, P Ciais, M Fader, RA Feely, T Gkritzalis, I Harris, J Hauck, T Ilyina, AK Jain, E Kato, V Kitidis, K Klein Goldewijk, C Koven, P Landschützer, SK Lauvset, N Lefèvre, A Lenton, ID Lima, N Metzl, F Millero, DR Munro, A Murata, JEMS Nabel, S Nakaoka, Y Nojiri, K O'Brien, A Olsen, T Ono, FF Pérez, B Pfeil, D Pierrot, B Poulter, G Rehder, C Rödenbeck, S Saito, U Schuster, J Schwinger, R Séférian, T Steinhoff, BD Stocker, AJ Sutton, T Takahashi, B Tilbrook, IT van der Laan-Luijkx, GR van der Werf, S van Heuven, D Vandemark, N Viovy, A Wiltshire, S Zaehle, and N Zeng (2015). " Global Carbon Budget 2015," Earth System Science Data 7, pp. 349-396 [doi:10.5194/essd-7-349-2015].

Lo, A.W. (1991). “Long term memory in stock market prices,” **Econometrica** 59, 1279-1313.

Palma, W. (2007). **Long-Memory Time Series: Theory and Methods**, Wiley Series in Probability and Statistics.

PNIRGHG (2018); “Portuguese National Inventory Report on Greenhouse Gas- 1990-2016, **Portuguese Environmental Agency** (APA), Lisbon.

PNEC2030 (2019). “Plano Nacional para a Energia e o Clima 2020-2030/National Plan for Energy and Climate,” **Agência Portuguesa do Ambiente**, Lisboa.

QEPiC 2030 (2015). “Quadro Estratégico da Política Climática,” **Agência Portuguesa do Ambiente**, Lisboa.

RNC2050 (2018). "Roteiro para a Neutralidade Carbónica/Roadmap for Carbon Neutrality," **Agência Portuguesa do Ambiente**, Lisboa.

Sowell, F. (1992a). "Modeling Long-Run Behavior with the Fractional ARIMA model," **Journal of Monetary Economics**, 29, 277-302.

Sowell F. (1992b). "Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models," **Journal of Econometrics**, 53, 165-188.

8. APPENDIX

Table A1 – Total CO_2 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	47.800	-0.6	4.1	8.5	41.1	54.5
2019	47.757	-0.7	4.9	10.3	39.7	55.8
2020	47.303	-1.7	5.8	12.2	37.8	56.8
2021	47.121	-2.0	6.5	13.8	36.4	57.9
2022	46.949	-2.4	7.3	15.5	35.0	58.9
2023	46.653	-3.0	8.0	17.2	33.5	59.8
2024	46.382	-3.6	8.7	18.8	32.0	60.7
2025	46.132	-4.1	9.4	20.4	30.7	61.6
2026	45.858	-4.7	10.1	21.9	29.3	62.4
2027	45.579	-5.2	10.7	23.5	28.0	63.2
2028	45.307	-5.8	11.3	25.0	26.7	63.9
2029	45.032	-6.4	11.9	26.5	25.4	64.6
2030	44.755	-6.9	12.5	27.9	24.2	65.3
2031	44.480	-7.5	13.1	29.4	23.0	66.0
2032	44.206	-8.1	13.6	30.8	21.8	66.6
2033	43.932	-8.7	14.1	32.2	20.7	67.2
2034	43.661	-9.2	14.7	33.6	19.6	67.8
2035	43.391	-9.8	15.1	34.9	18.5	68.3
2036	43.124	-10.3	15.6	36.2	17.4	68.8
2037	42.859	-10.9	16.1	37.6	16.4	69.3
2038	42.596	-11.4	16.5	38.8	15.4	69.8
2039	42.335	-12.0	17.0	40.1	14.4	70.3
2040	42.078	-12.5	17.4	41.4	13.4	70.7
2041	41.823	-13.0	17.8	42.6	12.5	71.1
2042	41.571	-13.6	18.2	43.9	11.6	71.6
2043	41.321	-14.1	18.6	45.1	10.7	72.0
2044	41.075	-14.6	19.0	46.3	9.8	72.3
2045	40.832	-15.1	19.4	47.4	9.0	72.7
2046	40.591	-15.6	19.7	48.6	8.1	73.0
2047	40.354	-16.1	20.1	49.8	7.3	73.4
2048	40.120	-16.6	20.4	50.9	6.5	73.7
2049	39.888	-17.1	20.7	52.0	5.8	74.0
2050	39.660	-17.5	21.1	53.1	5.0	74.3

Table A2 – CO_2 Emissions from Solid Fuels Forecasts for 2018-2050

Years	Total co2 emissions forecasts (f_t) (Mt)	Distançe to reference year: 2010 (%)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	10.697	69.8	1.6	14.8	8.1	13.3
2019	10.628	68.7	1.9	17.7	7.5	13.7
2020	10.476	66.3	2.2	20.8	6.9	14.1
2021	10.437	65.7	2.4	23.0	6.5	14.4
2022	10.365	64.6	2.6	25.4	6.0	14.7
2023	10.248	62.7	2.9	27.9	5.5	14.9
2024	10.156	61.2	3.1	30.1	5.1	15.2
2025	10.066	59.8	3.2	32.2	4.7	15.4
2026	9.961	58.2	3.4	34.4	4.3	15.6
2027	9.860	56.6	3.6	36.4	4.0	15.8
2028	9.764	55.0	3.7	38.4	3.6	15.9
2029	9.664	53.4	3.9	40.3	3.3	16.1
2030	9.565	51.9	4.0	42.2	2.9	16.2
2031	9.470	50.4	4.2	44.0	2.6	16.3
2032	9.375	48.8	4.3	45.8	2.3	16.4
2033	9.282	47.4	4.4	47.5	2.0	16.5
2034	9.191	45.9	4.5	49.2	1.8	16.6
2035	9.102	44.5	4.6	50.8	1.5	16.7
2036	9.015	43.1	4.7	52.4	1.3	16.8
2037	8.930	41.8	4.8	53.9	1.0	16.8
2038	8.848	40.5	4.9	55.4	0.8	16.9
2039	8.767	39.2	5.0	56.9	0.6	17.0
2040	8.689	38.0	5.1	58.3	0.4	17.0
2041	8.613	36.7	5.1	59.7	0.2	17.1
2042	8.539	35.6	5.2	61.0	0.0	17.1
2043	8.467	34.4	5.3	62.4	-0.2	17.2
2044	8.398	33.3	5.3	63.7	-0.4	17.2
2045	8.330	32.3	5.4	64.9	-0.6	17.2
2046	8.264	31.2	5.5	66.1	-0.7	17.3
2047	8.200	30.2	5.5	67.4	-0.9	17.3
2048	8.139	29.2	5.6	68.5	-1.0	17.3
2049	8.079	28.3	5.6	69.7	-1.2	17.3
2050	8.020	27.3	5.7	70.8	-1.3	17.4

Table A3 – CO_2 Emissions from Liquid Fuels Forecasts for 2018-2050

Years	Total co2 emissions forecasts (f_t) (Mt)	Distançe to reference year: 2010 (%)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	25.403	-13.1	2.8	10.9	20.8	30.0
2019	25.279	-13.6	3.4	13.3	19.7	30.8
2020	24.901	-14.8	4.0	15.9	18.4	31.4
2021	24.788	-15.2	4.5	18.0	17.4	32.1
2022	24.656	-15.7	5.0	20.2	16.5	32.8
2023	24.421	-16.5	5.5	22.5	15.4	33.4
2024	24.239	-17.1	6.0	24.6	14.4	34.0
2025	24.079	-17.7	6.4	26.7	13.5	34.6
2026	23.894	-18.3	6.9	28.7	12.6	35.2
2027	23.716	-18.9	7.3	30.8	11.7	35.7
2028	23.551	-19.5	7.7	32.7	10.9	36.2
2029	23.385	-20.0	8.1	34.7	10.0	36.7
2030	23.220	-20.6	8.5	36.6	9.2	37.2
2031	23.062	-21.1	8.9	38.5	8.5	37.7
2032	22.908	-21.7	9.2	40.3	7.7	38.1
2033	22.756	-22.2	9.6	42.1	7.0	38.5
2034	22.608	-22.7	9.9	43.9	6.3	38.9
2035	22.464	-23.2	10.2	45.6	5.6	39.3
2036	22.323	-23.7	10.6	47.3	5.0	39.7
2037	22.185	-24.1	10.9	49.0	4.3	40.1
2038	22.050	-24.6	11.2	50.6	3.7	40.4
2039	21.919	-25.0	11.4	52.2	3.1	40.7
2040	21.790	-25.5	11.7	53.8	2.5	41.1
2041	21.665	-25.9	12.0	55.3	1.9	41.4
2042	21.542	-26.3	12.2	56.9	1.4	41.7
2043	21.422	-26.7	12.5	58.3	0.9	42.0
2044	21.305	-27.1	12.7	59.8	0.3	42.3
2045	21.191	-27.5	13.0	61.3	-0.2	42.5
2046	21.079	-27.9	13.2	62.7	-0.6	42.8
2047	20.969	-28.3	13.4	64.1	-1.1	43.1
2048	20.862	-28.7	13.6	65.4	-1.6	43.3
2049	20.757	-29.0	13.9	66.8	-2.0	43.5
2050	20.655	-29.4	14.1	68.1	-2.5	43.8

Table A4 – CO_2 Emissions from Gas Forecasts for 2018-2050

Years	Total co2 emissions forecasts (f_t) (Mt)	Distançe to reference year: 2010 (%)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	7.570	-26.3	1.4	19.1	5.2	10.0
2019	7.381	-28.1	1.9	25.6	4.3	10.5
2020	7.202	-29.9	2.3	31.7	3.4	11.0
2021	7.030	-31.5	2.6	37.5	2.7	11.4
2022	6.863	-33.2	3.0	43.0	2.0	11.7
2023	6.701	-34.8	3.2	48.4	1.4	12.0
2024	6.544	-36.3	3.5	53.6	0.8	12.3
2025	6.390	-37.8	3.8	58.7	0.2	12.6
2026	6.240	-39.2	4.0	63.8	-0.3	12.8
2027	6.094	-40.7	4.2	68.7	-0.8	13.0
2028	5.951	-42.1	4.4	73.7	-1.3	13.2
2029	5.813	-43.4	4.6	78.5	-1.7	13.3
2030	5.678	-44.7	4.7	83.4	-2.1	13.5
2031	5.546	-46.0	4.9	88.2	-2.5	13.6
2032	5.418	-47.2	5.0	93.0	-2.9	13.7
2033	5.294	-48.5	5.2	97.8	-3.2	13.8
2034	5.173	-49.6	5.3	102.6	-3.6	13.9
2035	5.055	-50.8	5.4	107.4	-3.9	14.0
2036	4.941	-51.9	5.5	112.2	-4.2	14.1
2037	4.829	-53.0	5.7	117.0	-4.5	14.1
2038	4.722	-54.0	5.8	121.9	-4.7	14.2
2039	4.617	-55.0	5.8	126.7	-5.0	14.2
2040	4.515	-56.0	5.9	131.5	-5.3	14.3
2041	4.417	-57.0	6.0	136.4	-5.5	14.3
2042	4.321	-57.9	6.1	141.2	-5.7	14.4
2043	4.228	-58.8	6.2	146.1	-5.9	14.4
2044	4.138	-59.7	6.2	151.0	-6.1	14.4
2045	4.050	-60.6	6.3	155.9	-6.3	14.4
2046	3.966	-61.4	6.4	160.9	-6.5	14.5
2047	3.884	-62.2	6.4	165.8	-6.7	14.5
2048	3.804	-63.0	6.5	170.8	-6.9	14.5
2049	3.727	-63.7	6.6	175.8	-7.0	14.5
2050	3.652	-64.4	6.6	180.8	-7.2	14.5

Table A5 – CO_2 Emissions from Cement Production Forecasts for 2018-2050

Years	Total co2 emissions forecasts (f_t) (Mt)	Distançe to reference year: 2010 (%)	RMSE		Confidence interval (95%)	
			MtCO2	$rmse_t/f_t$ (%)	Lower limit	Upper limit
2018	2.759	20.7	0.9	30.9	1.4	4.2
2019	2.745	20.1	0.9	33.9	1.2	4.3
2020	2.731	19.4	1.0	36.0	1.1	4.3
2021	2.716	18.8	1.0	37.7	1.0	4.4
2022	2.702	18.2	1.1	39.1	1.0	4.4
2023	2.687	17.5	1.1	40.2	0.9	4.5
2024	2.673	16.9	1.1	41.2	0.9	4.5
2025	2.660	16.3	1.1	42.1	0.8	4.5
2026	2.646	15.7	1.1	42.9	0.8	4.5
2027	2.633	15.2	1.1	43.6	0.7	4.5
2028	2.620	14.6	1.2	44.3	0.7	4.5
2029	2.608	14.1	1.2	45.0	0.7	4.5
2030	2.596	13.5	1.2	45.6	0.7	4.5
2031	2.584	13.0	1.2	46.2	0.6	4.5
2032	2.572	12.5	1.2	46.7	0.6	4.5
2033	2.561	12.0	1.2	47.2	0.6	4.6
2034	2.551	11.6	1.2	47.8	0.5	4.6
2035	2.540	11.1	1.2	48.2	0.5	4.6
2036	2.530	10.7	1.2	48.7	0.5	4.6
2037	2.520	10.2	1.2	49.2	0.5	4.6
2038	2.511	9.8	1.2	49.6	0.5	4.6
2039	2.502	9.4	1.3	50.0	0.4	4.6
2040	2.493	9.0	1.3	50.5	0.4	4.6
2041	2.484	8.6	1.3	50.9	0.4	4.6
2042	2.476	8.3	1.3	51.2	0.4	4.6
2043	2.467	7.9	1.3	51.6	0.4	4.6
2044	2.459	7.6	1.3	52.0	0.4	4.6
2045	2.452	7.2	1.3	52.4	0.3	4.6
2046	2.444	6.9	1.3	52.7	0.3	4.6
2047	2.437	6.6	1.3	53.1	0.3	4.6
2048	2.430	6.3	1.3	53.4	0.3	4.6
2049	2.423	6.0	1.3	53.7	0.3	4.6
2050	2.416	5.7	1.3	54.0	0.3	4.6

GEE Papers

Gabinete de Estratégia e Estudos