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Reference forecasts for CO_2 emissions from fossil-fuel combustion and cement production in Portugal

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ABSTRACT

We provide reference forecasts for CO_2 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 reference 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 39.9 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 31.5 Mt of CO_2 will require additional policy efforts. Accordingly, our results suggest that about 65.5% 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.

1. Introduction

The purpose of this article is to provide reference forecasts for CO_2 emissions in Portugal. 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)].

Recently, the Intergovernmental Panel on Climate Change [see IPCC (2018)] has pointed out 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 CO_2 would need to fall by about 45% from 2010 levels by 2030, reaching 'net zero' around 2050. These new targets were, in general terms, incorporated into the Roadmap for Carbon Neutrality, released as a Portuguese Ministerial Council Resolution in July 2019 [RNC2050, 2019].

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 reference or baseline scenario. We follow the IPCC definition of baseline scenario, which assumes that no mitigation policy or measure beyond those that are already in place and/or legislated or planned for implementation. 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 reference scenario 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 autoregressive fractionally integrated moving

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average approach [ARFIMA], to provide reference forecasts for CO_2 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 CO_2 emissions). In addition, this methodology recognizes that emission patterns are subject to a great degree of inertia due to consumption patterns and production technologies. Accordingly, a focus on a methodology that highlights the relevance of long-term dynamics is fundamental.

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, 2017)].

In this literature, 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 [see among others, Baillie (1996), Diebold and Rudedusch (1989) and Delgado and Robinson (1994)]. The intensity of this phenomena can be measured by a differencing parameter, which includes the stationary and the non-stationary cases as particular cases.

'Long memory' means that there is significant dependence between observations widely separated in time, and from a policy perspective, the effects of shocks are temporary but long lasting. Therefore, the only way to achieve permanent effects is to adopt permanent policies. In contrast, the traditional stationary/non-stationary dichotomy would suggest that the effects of transitory policies are either short-lived (stationary case) or permanent (non-stationary case). This more rigid approach is bound to lead to misleading policy implications by either identifying short lived effects where the effects may actually be long lasting or by identifying as permanent, effects that may actually be mean reverting. Accordingly, the fractional integration properties of CO_2 emissions have important policy implications for the specification of long-term reference case scenarios for emissions.

All of these issues are of great relevance in the context of the Portuguese experience. 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) and the Roadmap for Carbon Neutrality, RNC2050 (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, and the participation in the European Union Emissions Trading Scheme. 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. Still, there is a keen awareness that there is much to be done.

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

Aggregate CO_2 emissions in Portugal are the sum of four components: CO_2 emissions from burning fossil fuels – solid/coal, liquid/oil, and gas, and CO_2 emissions from cement production. There are no CO_2 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.

We consider annual data for CO_2 emissions in Portugal for the period between 1950 and 2017. The data until 2014 is from the Carbon-Dioxide Information Analysis Centre - CDIAC [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.

We obtained emissions between 2015 and 2017 by using the information reported in the National Inventory of GHG Emissions, PNIRGHG (2019). While this source only goes back to 1990 and, therefore, in and of itself provides a rather inadequate sample size, it is a very helpful source in extending the CDIAC series. We started by checking the consistency of the two data series for the period they overlap, i.e., 1990–2014. We find they are very closely related something to be expected as the central sources of information for the CDIAC are the national inventory reports. Specifically, the two series are statistically cointegrated in growth rates. With this in mind, we obtain the values for the different emissions for 2015–2017 by simply applying the growth rates of CO2 emission from the PNIRGHG (2019) figures for CO2 emission levels without net CO2 from land use, land use change and forestry.

2.2. Description of the data

Table 1 presents summary information about our data. It includes information about total CO_2 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.

In the second half of the 20th Century, total CO_2 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. Annual CO_2 emissions peaked in 2002 at 66.7 Mt. By 2017, emissions reached 50.8 Mt, a Fig. 20% and 5.6% above the 1990 and 2010 reference levels, respectively. For perspective, Portugal's total CO_2 emissions in 2017 represent about 1.4% of total European Union emissions and just 0.13% of worldwide emissions.

CO_2 emissions from solid fossil fuel combustion represented on average over the sample period a little more than 18.6% of total

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

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 they represented close to 80% of the total, 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

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

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 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 autoregressive fractionally integrated moving average model is a generalization of the autoregressive moving average [ARMA] 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 autoregressive components alone are important to assess whether or not the series is stationary. In the case of the ARFIMA model, the autoregressive and the moving average 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 dynamic 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 autoregressive moving average process of order p and q, then $\{x_t\}$ is a ARFIMA$(\mathrm{p}, \mathrm{d}, \mathrm{q})$ process:

$$\varphi(L)(1-L)^d x_t = \theta(L)e_t$$

where

$$\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \ \ldots \ - \varphi_p L^p = 0 \quad \theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ \ldots \ + \theta_p L^q = 0$$

are the polynomials of order p and q respectively, 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 φ, θ, d, β and σ^2 is done by the method of maximum likelihood. The log-Gaussian likelihood of y given parameter estimates $\widehat{\eta} = (\widehat{\varphi}, \widehat{\theta},\ \widehat{d},\ \widehat{\beta},\ \widehat{\sigma}^2)$ was established by Sowell (1992b) as

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

where $\boldsymbol{X}$ 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 $\boldsymbol{D} = \mathrm{Diag}(\nu_t)$ and $\boldsymbol{L}$ is lower triangular, so that;

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

Moreover, let $\tau_t = V_t^{-1}\gamma_t$, $\gamma_t = (\gamma_1,\ \gamma_2,\ \ldots,\ \gamma_t)'$ 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 $x,\ x_2,\ \ldots x_t$ is

$$\widehat{f}_{t+1} = \sum_{k=1}^{t} \tau_{t,k} f_{t-k+1}$$

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

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

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

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. Preliminary structural break analysis

Preliminary Quandt-Andrews and Andrews-Ploberger tests for structural changes [see Andrews (1993) and Andrews and Ploberger (1994)] are reported in Table 2. These tests point to possible structural breakpoints for total CO_2 emissions, emissions from liquid fuels and from cement production in 2002, for coal in 1995 and for cement production in 2008.

From a conceptual perspective, these are all reasonable structural break points. The year 2002 corresponds to a turning point in total CO_2 emissions in Portugal due to the full implementation of the international commitments under the Kyoto Protocol and the European Union effort sharing decisions. In turn, 1995 corresponds to the beginning of activity of the Pego power plant, one of the only two coal-operated power plants in the country. Finally, in 2008 there was a sharp decline in the production of cement, due to the economic and financial crisis and its devastating effects on the construction sector.

4.2. Fractional integration analysis

Table 3 presents the results of the estimations of the ARFIMA(p, d, q) models, using annual data from 1950 to 2017. The best specifications were selected using the Schwartz Bayesian Information Criterion [BIC] and include statistically significant autoregressive and moving-average terms.

When included in the ARFIMA models, however, the dummy coefficients corresponding to the potential structural breaks identified in the previous section 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. Not surprisingly, the corresponding estimation results with structural breaks are not different in any meaningful way [and are available from the authors upon request].

Table 2
Quandt-Andrews and Andrews-Ploberger structural break tests.

Variable	Break point	Quandt-Andrews		Andrews-Ploberger	
		t-test	p-value	*t*-test	p-value
Aggregate CO2 emissions	2002	18.981	0.002	6.430	0.002
CO2 emissions from solid fuels	1995	13.029	0.027	4.050	0.021
CO2 emissions from liquid fuels	2002	13.117	0.026	3.475	0.038
CO2 emissions from gas fuels	2011	3.276	0.847	1.086	0.481
CO2 emissions from cement production	2008	22.571	0.000	7.786	0.001

Overall, our results provide strong empirical evidence for the non-rejection of the presence of long memory for both aggregate CO_2 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 CO_2 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.

4.3. In-sample global CO_2 emissions forecasts

Fig. 1 plots the actual values against the in-sample forecasts for global CO_2 emissions between 1950 and 2017. Table 4 summarizes our forecasting accuracy analysis for the in-sample predictions.

In general, we get excellent in-sample predictions for both aggregate CO_2 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 CO_2 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 CO_2 emissions until 2050. The detailed results are presented in Fig. 2 and Tables A1 to A5 in the Appendix. In Table 5, we present summary results relative to the 2010 reference emissions. To facilitate comparisons, we follow the lead of the IPCC (2018) report, which considers 2010 as the reference year for emissions reductions targets.

Total CO_2 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 17.5% below the 2010 reference level (48.1 Mt), 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

Table 3
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
	p₁	0.602	0.138 (*0.000*)	[0.331; 0.873]	
	p₃	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
	p₁	0.479	0.135 (*0.000*)	[0.215; 0.743]	
	p₃	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
	p₁	0.532	0.099 (*0.000*)	[0.337; 0.727]	
	p₃	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
	p₁	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
	p₁	0.497	0.126 (*0.000*)	[0.250; 0.744]	

Note: *p* stands for the estimated value of the parameter associated with the x_{t-p} term of the autoregressive component.

annual reduction of 0.26 Mt.

The general pattern of reductions projected for total emissions is also present, with some minor changes, at a more disaggregated level when we consider the four different individual components of total emissions. Noticeably, we project emissions for liquid fuel and gas fuel combustions to be always below the 2010 reference levels. In turn, we project 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 to 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 (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 of global net anthropogenic CO2 emissions by about 45% from 2010 by 2030, and reaching 'net zero' around 2050. While the IPCC report focuses on global anthropogenic emissions as the reference variable, our projections focus only on CO2 emissions from fossil fuel combustion and cement production, to which we apply literally the broader IPCC goals. As such, in this exercise we ignore any national or source-based differentiation in the international implementation of the IPCC2018 targets.

The IPCC2018 emissions targets were applied and adopted in very general terms to the Portuguese case in the RNC2050 (2019), which establishes the strategic framework of public policies in Portugal aiming at carbon neutrality in 2050. In reality, the RNC2050 (2019) does not set specific targets for 2030 and 2050, but rather provides confidence intervals based on three alternative scenarios. Specifically, the RNC2050 (2019) points for 2030 to a range of reduction in emissions of [-45%,-55%] and to carbon neutrality by 2050 assuming a range in carbon sinks of [-85%,-90%], both relative to 2005. We apply the middle points of these ranges to the values for CO2 emissions from fossil fuels and cement production in 2005 to obtain the implicit RNC2050 targets for 2030 and 2050. Then, we change the base year from 2005 to 2010 in order to facilitate comparisons. According to these calculations, the RNC2050 targets represent a reduction of 32.2%% in emissions by 2030 while carbon neutrality by 2050 requires a reduction of 83.0%, both relative to 2010 levels. Ultimately, the RNC2050 (2019) 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.

The IPCC2018 and the RNC2050 policy targets are presented in lines 1 and 2 of Table 6. Under the IPCC targets, CO_2 emissions in Portugal would have to decrease by 21.6 Mt or 45% of 2010 emissions by 2030 and a further 18.3 Mt, or a further 38% of 2010 levels, between 2030 and 2050. The total target accumulated reduction by 2050 is 39.9 Mt, which corresponds to a reduction of 83% relative to 2010. Given our discussion about and without loss of generality, we can say that 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, however, is slightly less frontloaded, with a projected decrease of 32.2% in 2030 relative to 2010 values.

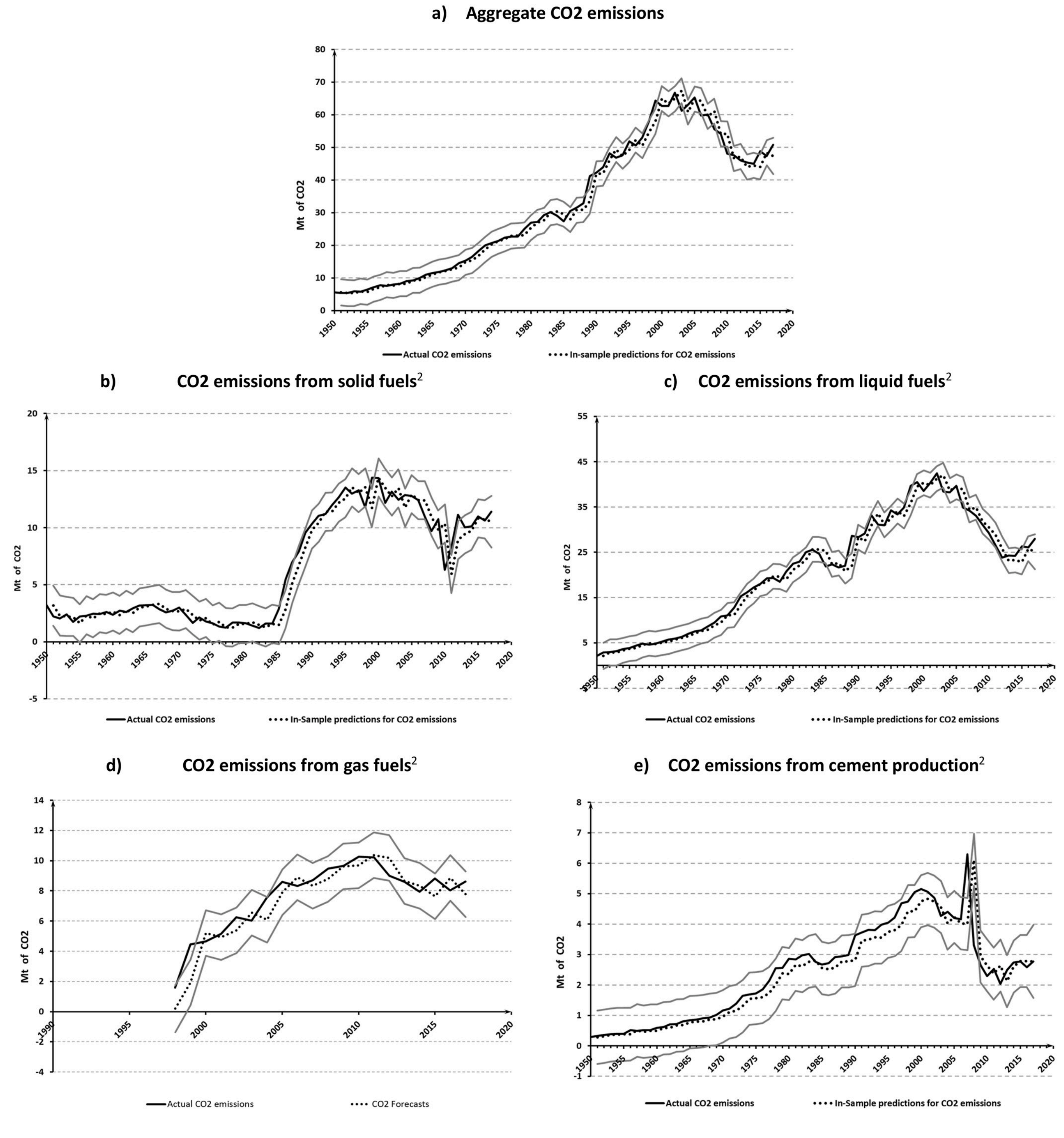
Of the greatest importance is the comparison of these policy targets with our reference scenario. Line 3 of Table 6 indicates that the inertia effect estimated according to the ARFIMA model projections is responsible for the reduction of 6.9% of emissions by 2030 and of 10.5% between this year and 2050, with a total cumulative reduction of 17.5%. 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 CO_2 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 6 and represents the difference between the IPCC and the RNC2050 policy targets and the ARFIMA model forecasts, respectively.

Line 4 of Table 6 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 27.4% relative to 2030 emission levels, while inertia will be responsible for reducing the remaining 10.6% of emissions this year. Accordingly, the inertia of the system will lead to just 17.5% of the total target reduction in emissions necessary by 2050 and the remaining efforts (-65.5%) will have to come from deliberate decarbonization policies.

Moreover, our results indicate that to meet the RNC2050 (2019) mid-term targets in 2030, it is necessary a policy effort that leads to a reduction of CO2 emissions of 32.2% relative to 2010 levels. Of these, 25.3% corresponds to the extra effort over the basic RNC2050 reduction target due to the inertia of the emissions system. To achieve carbon neutrality by 2050 will require an extra reduction of CO2 emissions of 50.5% relative to 2010 levels, 40.2% of which from deliberate decarbonization policies, and the remaining 10.6% will be achieved through the inertia of the emissions system.

Finally, it should also be noted that the new IPCC guidelines impose a



Note: The grey lines represent the upper and lower bounds of the 95% confidence interval.

Fig. 1. In-sample CO2 Predictions: 1950-2017
Note: The grey lines represent the upper and lower bounds of the 95% confidence interval.

more stringent policy effort until 2030 - a 2.5% average annual reduction in emissions than the subsequent 20 years – a 1.9% 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 CO_2 emissions from fossil fuel combustion – coal, oil, and gas - and cement production in Portugal, and to make projections of CO_2 emissions until 2050. These ARFIMA projections allow us to assess

Table 4
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%

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 decarbonization 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 65.5% of the 2010 levels. The required long-term policy effort is the same for the IPCC2018 and RNC2050 since both have essentially the same objective for emissions in 2050. The direct application to Portugal of the IPCC2018 targets, however, requires a larger additional policy effort by 2030 (-45% relative to 2010 level) and, consequently, lower additional policy effort in the subsequent 20 years (-38% relative to 2010 levels) compared to the RNC2050 targets (-32.2% and -50.8%, respectively, relative to 2010 levels). Accordingly, if directly applied to Portugal, the IPCC2018 targets would lead to the need of frontloaded policies until 2030. By contrast, with the RNC2050 targets the greatest efforts would have to occur between 2030 and 2050.

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. Trivially, the results confirm 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. Accordingly, but not surprisingly, our forecasts support the contention of the IPCC (2018) report that active and 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 65.5% of the 2010 reference levels - are very demanding and frontloaded if the IPCC2018 targets were to be strictly adopted. 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.

Policy efforts toward the decarbonization of the Portuguese economy must necessarily include important changes such as a comprehensive elimination of pervasive fossil fuel subsidies; the elimination of the large market distortions present in electricity pricing; discontinuing coal-operated electricity production; continued promotion of electricity production from renewable sources; the promotion of abundant and readily available energy efficiency measures. Ultimately, they will require the establishment of a meaningful carbon emissions pricing - either though carbon taxation or emission trading markets.

Significantly, the Portuguese government announced the forced closure of the two major coal-operated power plants - Pego by 2021 and Sines by 2023. This is an important step in the right direction as these two power plants account for about 19% of the emissions in the country. Furthermore, this is a permanent change, the type of change necessary in light of the long-term memory of the emissions systems. Nevertheless, these forced closures will lead to a reduction in emissions that is less than 25% of the total reductions deemed as necessary under our projections.

This paper provides an application and important implications for policy making for the case of the Portuguese emissions. Its relevance, however, is far from parochial. In fact, the need to identify a meaningful reference scenario for emissions is universal. Prospective mitigation policy assessment always requires identifying a benchmark scenario for emissions to determine the timing and magnitude of the policy efforts that are necessary. Defining a meaningful benchmark is best achieved by identifying a reference scenario reflecting the emissions that would exist at future dates in the absence of any emission targets and policies rather than using a recorded value in a particular year [see, for example, Markandya (2019)]. The method presented in this paper has the advantage of generating such a reference scenario and one that reflects the long-term memory of the emissions system. Considering the long-term memory of the system is critical not only for the formulation of the most accurate reference forecasts but also for the understanding of the nature of the response of the emissions system to large policy changes or systemic shocks.

Naturally, our method of identifying the reference scenario and concomitantly the policy efforts to achieve the necessary emission targets is not without limitations. First and foremost, by focusing on the inertia from the past, our approach may miss some of the dynamics in the direction of greater environmental awareness and more environmental conscientious behaviors fueled by social media in the recent past. Our results suggest, however, that the wide gulf between the current emissions patterns and the current future emissions targets is highly unlikely to be bridged without clear, deliberate, comprehensive and substantial policy efforts. As such, identifying the timing and magnitude of these policy efforts requires a frequent update of the reference forecasts in light of the availability of new data, the implementation of new policies, and the consideration of potential exogenous shocks. For example, policies of the type of the forced closure of the coal-operated power plants in Portugal and exogenous shocks such as the COVID-19 pandemic, while may or may not affect the inertia of the emissions system represent significant structural change that need to be considered in the development of future reference forecasts.

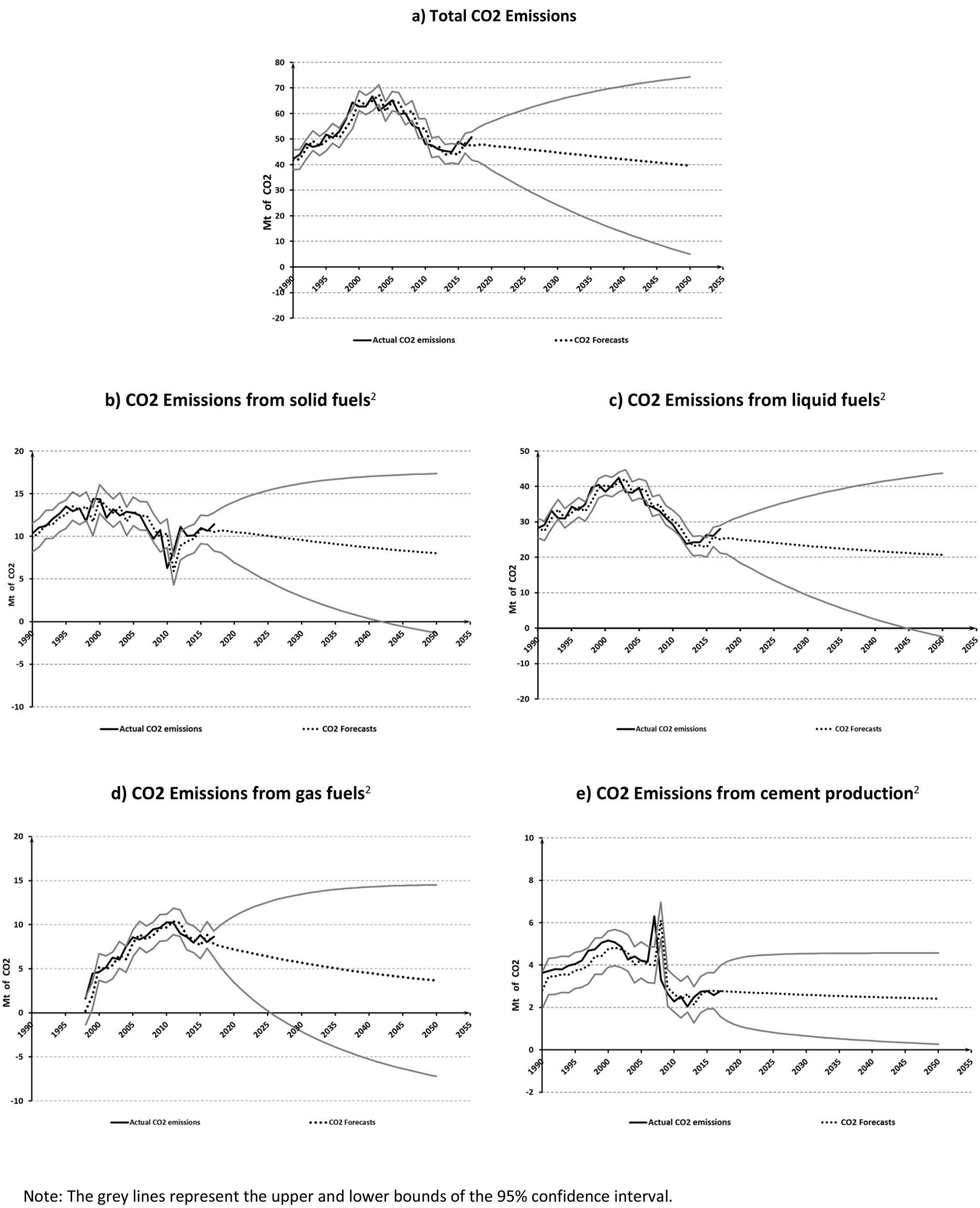


Fig. 2. CO_2 emissions forecasts: 2018 - 2050
Note: The grey lines represent the upper and lower bounds of the 95% confidence interval.

Table 5
CO2 emissions forecasts: Changes in emissions relative to 2010 reference levels (%).

	Aggregate CO2	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

Table 6
Reductions in CO2 emissions relative to 2010 (%).

	2030	2050	
		Increment over 2030	Total
(1) IPCC (2018) Policy targets	-45.0%	-38.0%	-83.0%
(2) RNC2050 (2019) targets	-32.2%	-50.8%	-83.0%
(3) ARFIMA model	-6.9%	-10.6%	-17.5%
Policy efforts relative to ARFIMA model			
(4) IPCC (2018) targets (1)–(3)	-38.1	-27.4%	-65.5%
(5) RNC2050 (2019) targets (2)–(3)	-25.3	-40.2	-65.5%

Declaration of competing interest

None.

CRediT authorship contribution statement

José M. Belbute: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Alfredo M. Pereira:** Conceptualization, Methodology, Writing - review & editing.

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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

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