Updated Reference Forecasts for Global CO_2 Emissions from Fossil-Fuel Consumption(*)

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Abstract

We provide alternative reference forecasts for global CO_2 emissionsbased on an ARFIMA model estimated with annual data from 1750 to 2014. These forecasts are free from additional assumptions on demographic and economic variables that are commonly used in reference forecasts, as they only rely on the properties of the underlying stochastic process for CO_2emissions, as well ason all the observed information it incorporates. In this sense, these forecasts are morebased on fundamentals. Our reference forecast suggests that in 2030, 2040 and 2050, in the absence of any structural changes of any type, CO_2would likely be at about 23.1%, 29.1% and 33.7% above 2010 emission levels, respectively. These values are clearly below the levels proposed by other reference scenarios available in the literature.This is important, as it suggests that the ongoing policy goals are actually within much closer reach than what is implied by the standard CO_2reference emission scenarios. Having lower and more realistic reference emissions projections not only gives a truer assessment of the policy efforts that are needed,but also highlights the lower costs involved in mitigation efforts, thereby maximizing the likelihood of more widespread energy and environmental policy efforts.

Keywords: Forecasting, reference scenario, CO_2 emissions, long memory, ARFIMA.
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1. Introduction

There is a great degree of debate on how to specify long-term reference case scenarios for CO_2 emissions. This is critical first step in ascertaining the extent of the policy effort required to achieve any policy target for CO_2 emissions, and thereby determining the costs involved in achieving such goals.

In the most fundamental sense,specifying a reference scenario means forecasting a path forCO_2emissions that reflects not only the existing economic and demographic trends, but also theongoing emissions policies. Most reference case forecasts, however, are based on a multivariate approach and include alternative economic and demographic assumptions, as well as very often even new policy commitments as in the typical "business as usual" projections [see, for example, International Energy Agency (2015), OECD (2012), and Energy Information Agency of the US Department of Energy (2014)]. The problem with this conventionalapproach to establishing reference scenarios is that it introduces rather a great degree of arbitrariness in their definition, and thereby clouds the information it intends to provide – specifically, the extent of the efforts needed and the corresponding costs.

This paperuses an ARFIMA approach to providereference forecasts for global CO_2emissions based on a univariate analysis, recognizing the presence of long-memory through fractional integration. Our forecasts for CO_2emissions are strictly based on the most basic statistical fundamentals of the stochastic process that underlies global CO_2emissions. As such, our forecasts capture the information included in the sample, and implicitly assume that the observed trends will continue in the future. Thus, these forecasts provide the most fundamental reference case forecast of CO_2emissions.

The ARFIMA methodology we adopt is inspired by a budding literature on the analysis of energy and carbon emissions based on a fractional integration approach[see, for example, Elder and Serletis (2008), Lean and Smyth (2009), Gil-Alana et al. (2010), Barassi et al.(2011), Apergis and Tsoumas (2011, 2012), Barros et al. (2012a, 2012b, 2016) and Gil-Alana et al. (2015)]. Measuring the persistence of CO_2emissions is of utmost importance for the design of energy and environmental policies aiming at reducing the economy's carbon intensity. If CO_2emissions 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 CO_2emissions 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 goeswell beyond the I(0) stationary/I(1) non-stationary dichotomy to consider the possibility that variables may follow a long memory process. 'Long memory' means a significant dependence between observations widely separated in time, and, therefore, the effects of policy shocks may be temporary but long lasting.

This paper is a greatly expanded and updated version of Belbute and Pereira (2015). It provides much greater detail on the data set, methodological approach, empirical results, and policy implications. More importantly, it updates the CO_2 emissions forecasts by considering first, more recent CO_2 emissions data just released and second, by accommodating structural breaks, namely in 1946, in the estimation of the basic ARFIMA model.

2. Data: Sources and Description

2.1 Data Sources

In this paper, we use annual data for the world's overall CO_2 emissions from fossil-fuel consumption covering 1751 to 2014. Data were compiled from the Carbon-Dioxide Information Analysis Centre [see Le Quére et al. (2015)].See Joint Research Centre of the European Commission (2014) for a detailed comparison among different available measurements of CO_2 emissions.

Aggregate CO_2 emissions are defined as a sum of five global CO_2 emissions components: CO_2 emissions from burning fossil fuels (solid, liquid, gas and gas flaring) and from cement production. The data do not consider emissions from land use, nor a change in the use of land, or forestry, or emissions from international shipping or bunker fuels. All variables are measured in million metric tonnes of carbon per year (Mt, hereafter),and were converted into units of carbon dioxide (CO_2) by multiplying the original data by 3.664, the ratio of the two atomic weights.

2.2 Description of the Data

Summary information is presented in Table 1. The first column of shows the mean value of the world total CO_2 emissions for each of the twenty six decades of the sample, while the remaining columns show the shares of emissions from fossil fuel combustion (coal, oil, gas and gas flaring) and cement production.

Before the Industrial Era, i.e., before 1751,CO_2 emissions were mostly stable over time, and caused by the release of carbon into the atmosphere from deforestation and land-use activities [see Ciais et al. (2013)]. Over the past two and a half centuries, however, the world's total CO_2 emissions have increased dramatically, rising from just 11 Mt in 1751 to a staggering 38,900 Mt in 2014. The average rate of growth for the whole-period sample was 3.12% per year. For the more recent period from 2000 to 2014, the annual growth rate was slightly lower, at 2.68%.

This aggregate increase in CO_2 emissions hides a variety of important underlying trends throughout the sample period. During the period of thefirst industrial revolution, i.e., between 1751 and the 1830s, total CO_2 emissionsremained stable, with levels ranging from 11 Mt in 1751 to nearly 96 Mt towards the end of the 1830s. The period of the second industrial revolution, i.e., from 1870 to 1900, brought with it two greatly influential inventions – electricity and the internal combustion engine. These inventions, along with the outburst of innovation they induced, triggered a widespread use of fossil fuels, either as source of energy or as a raw material in the production of plastics, detergents, paints or asphalts. Accordingly, CO_2 emissions have since grown exponentially.

During theperiod of the two industrial revolutions, coal became the ubiquitous source of CO_2 emissions, accounting for 100% of total CO_2 emissions until the early 1860s,and remained a dominant source of emissions until the present times. For the sample period, coal accounted for 83.04% of CO_2 emissions. When considering only the period following World War II, coal accounted for 44.50% of all CO_2 emissions. Having reached an historical low in 1974 representing 34.16% of all emissions, it rebounded to reach41.93% in 2014.

CO_2 emissions from oil combustion started in the 1860s, and after 1920 became a significant source of energy. It represents 21.86% of the world's aggregate CO_2 emissions for the entire sample period, but has increased at a consistent pace. If we consider only the period following World War II, oil combustion has represented an average of 38.17% of all emissions. In 2014, the CO_2 emissions from liquid fuel consumption accounted for 37.01% of total emissions.

Gas-fuel consumption includes both liquefied petroleum gas and more recently, natural gas. It is responsible for 7.95% of aggregate CO_2 emissions for the entire sample period. It became a much more significant source of emissions after the 1950s, a period during which it accounted for 13.60% of all emissions. It reached a peak in 1999 with 19.07%, but since then has remained relatively stable. In 2014 it accounted for 18.67% of emissions.

Finally, CO_2 emissions from cement production and gas flaring are more residual. They account for a combined total of around 3.45% of total emissions for the whole sample period. If we consider only the period after World War II, emissions from cement production and gas flaring account for an average of 2.57% and 1.23%, of total emissions, respectively.

2.3 On the Possibility of Structural Breaks

Naturally, in such a long sample period, many changes have occurredwhich may have led to structural breaks. It includesyears of the two industrial revolutions, the period of the 1929 crisis and the depression that followed, as well as World War II. Chow tests suggests the existence of two potentiallyimportant structural breaks at around 1830 and 1946, consistent with the end of the first industrial revolution and the end of the World War II, respectively. Detailed test results are available from the authors upon request.

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 with an autocorrelation function that exhibits persistence, albeit neither as an I(0) or an I(1) process. Nevertheless, its persistence is consistent with a stationary process, where the autocorrelations decay hyperbolically. Because the autocorrelations die out slowly, the fractionally-integrated processes display long-run rather than short-term dependence, and for that reason are also known as long-memory processes[see, for example, Sowell (1992a), (1992b), Baillie (1996), and Palma (2007)].

A time series $x_t = y_t - \beta z_t$–where β is the coefficients vector, z_t represents all deterministic factors of the process, y_t, and $t = 1, 2, \dots n$, − issaid 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, L is the lag operator, d is a real number that captures the long-run effect, and u_t is $I(0)$.

Through binomial expansion, the $(1-L)^d$ filter provides an infinite-order L polynomial with slowly and monotonically-declining weights,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2!} L^2 - \frac{d(d-1)(d-2)}{3!} L^3 + \cdots \tag{2}$$

and thus (1) can be rewritten as:

$$x_t = d x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \frac{d(d-1)(d-2)}{3!} x_{t-3} + \cdots u_t. \tag{3}$$

If d is an integer, then x_t is a function of a finite number of past observations. In particular, if $d = 1$, then x_t is a unit root non-stationary process and, therefore, the effect of a random shock is exactly permanent. If $d = 0$, then $x_t = u_t$, and the time series is $I(0)$ and weakly auto-correlated (or dependent) with autocovariances that decayexponentially. More formally,

$$\gamma_j = {\alpha_1}^j, \qquad \text{for} \quad j = 1, 2, \dots. \text{ and } |\alpha_1| < 1. \tag{4}$$

Allowing d to be a real number provides a richer degree of flexibility in the specification of the dynamic nature of the series, and depending on the value of d we can determine different levels of intertemporal dependency. In fact, when d is a non-integer number, each x_t depends on its past values way back in time. Moreover, the autocovariance function satisfies the following property

$$\gamma_j \approx c_1 j^{2d-1}, \qquad \text{for } \ j = 1, 2, \dots \ \text{ and } \ 0 < |c_1| < \infty \tag{5}$$

Where≈ means that the ratio between the two sides of (5) will tend to unity as $j \to \infty$. Assuming that process x_t has a spectral distribution such that the density function $f(\lambda)$ is given by

$$f(\lambda) = \left(\frac{\sigma^2}{2\pi}\right) \left|\frac{\theta \ \left(e^{-i\lambda}\right)}{\phi \ \left(e^{-i\lambda}\right)}\right|^2 [2(1 - \cos(\lambda)]^{-2d} \tag{6}$$

then, for low frequencies, as $\lambda \to 0^+$, we obtain

$$f(\lambda) \approx c_2 \lambda^{-2d} \tag{7}$$

where, $c_2 = \left(\frac{\sigma^2}{2\pi}\right) \left|\frac{\theta(1)}{\phi(1)}\right|^2 > 0$ and ≈ means that the ratio between the two sides of (7) will tend to unity as $\lambda \to 0^+$.

In general, larger values for the fractional-difference parameter, d, indicate a greater degree of persistence. 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 processreverts 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$d \geq 1$, then the process is non-stationary and non-mean-reverting, i.e. the effects of random shocks are permanent.

3.2 ARFIMA Processes

An autoregressive fractionally-integrated moving average process, ARFIMA, is an extension of the traditional ARIMA model by allowing for fractional degrees of integration. The autocorrelations of the ARFIMA process decay at a slower rate than the exponential rate associated with the ARMA process and, generally, with short memory processes. ARFIMA models were first introduced to solve problems with unit roots tests caused byeither variable aggregation or by the duration of shocks [see, again, Palma (2007)].

A process like (1) is called fractionally integrated of order d if d is a non-integer. If, in addition, u_t in (1) is an$ARMA(p, q)$, then x_t is an ARFIMA process and can be written as

$$\phi(L)(1-L)^d x_t = \theta(L)e_t \tag{8}$$

where$\phi(L)$ and $\theta(L)$ are the polynomials of order p and q respectivelly, with all zeroes of $\phi(L)$ and $\theta(L)$ given, respectively, by

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ \ldots \ - \phi_p L^p = 0 \tag{9}$$

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ \ldots \ + \theta_p L^q = 0 \tag{10}$$

lying outside the unit circle, and with $e_t$as white noise. Clearly, the process is stationary and invertible for $-0.5 < d < 0.5$.

In this paper the parameters of the ARFIMA model are jointly estimated by a time-domain Maximum Likelihood method.The log Gaussian likelihood was established by Sowell (1992a) and is

$$\ell\big((y|\hat{\eta})\big) = -\frac{1}{2}\left\{\boldsymbol{T}\log(2\pi) + \log\left|\widehat{\boldsymbol{V}}\right| + \big(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}\big)'\widehat{\boldsymbol{V}}^{-1}\big(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}\big)\right\} \tag{11}$$

The covariance matrix$\boldsymbol{V}$ has a Toeplitz structure:

$$\boldsymbol{V} = \begin{bmatrix} \gamma_0 & \gamma_1 & \gamma_2 & \cdots & \gamma_{T-1} \\ \gamma_1 & \gamma_0 & \gamma_1 & \cdots & \gamma_{T-2} \\ \gamma_2 & \gamma_1 & \gamma_0 & \cdots & \gamma_{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{T-1} & \gamma_{T-2} & \gamma_{T-3} & \cdots & \gamma_0 \end{bmatrix} \tag{12}$$

where, $\gamma_0 = Var(y_t)$ and $\gamma_j = Cov(y_t, y_{t-1})$ for $j = \ 1, 2, \ldots \ t-1$ and $t = 1, 2, \ldots \ T$.

3.3 The Impulse Response Functions

An important advantage of ARFIMA models is the flexible nature of the impulse-response weights, which provide useful information about the impact ony_t following a one-time change in the innovations, holding everything else constant. Indeed using (1), (8), (9) and 10), the ARFIMA process can be rewritten as

$$y_t = \beta z_t + (1 - L)^{-d}\, \psi(L) e_t \qquad (13)$$

where $\psi(L) = \frac{\theta(L)}{\phi(L)} = (1 + \psi_1 L + \psi_2 L^2 + \ \dots\ )$ and the coefficients ψ_i are jointly referred to as the impulse-response function of the traditional ARMAprocess. Accordingly, the impulse-response function for an ARFIMA process corresponds to a fractionally-differentiated impulse-response function for an ARMA model by applying the filter $(1 - L)^{-d}$ to $\psi(L)$ [see Hassler and Kokoszka (2010)].In the presence offractional differentiation, the coefficients ψ_i decay very slowly.

3.4 Accommodating Structural Breaks

The existence of structural breaks is likely to lead to biased parameter estimates [see, for example, Perron (1989), and Leybourne and Newbold (2003)]. In the context of fractional integration, the issue has mostly been approached in the context of their forecasting capability [see, for example, Gabriel and Martins (2004), and Bisaglia and Gerolimetto [2005)]. Critically, from our standpoint, there is evidence suggesting that ignoring structural breaks in the deterministic components may lead to the over-estimation of the fractional integration parameter, and thereby finding in favor of long memory [see, for example, Granger and Terasvirta (1999), Granger and Hyung (2004), Diebold and Inoue (2001), Gourieroux and Jasiak (2001), and Charfeddine and Guégan (2012)].

In our approach, structural breaks are incorporated in the ARFIMA framework by introducing dummies in the deterministic component z_t in equation (13), corresponding to breaks in the constant and in the trend.We allow for three cases – abreak only in the constant (crash effect), a break only in the trend (growth effect), a break in both constant and trend (crash and growth effects).

3.5 ARFIMA Forecasting and Prediction-Accuracy Assessment

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

$$\boldsymbol{L}' = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ \tau_{1,1} & 1 & 0 & \dots & 0 \\ \tau_{2,2} & \tau_{2,1} & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tau_{(T-1),(T-1)} & \gamma_{(T-1),(T-2)} & \tau_{(T-1),(T-3)} & \dots & 1 \end{bmatrix} \quad (14)$$

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

Let $z_t = y_t - x_t\beta$. The best linear forecast of z_{t+1} based on $z_1, z_2, \dots\ z_t$ is

$$\hat{z}_{t+1} = \sum_{k=1}^{t} \tau_{t,k} z_{t-k+1} \quad (15)$$

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

$$\hat{y} = L^{-1}\big(y - X\hat{\beta}\big) + X\hat{\beta}. \quad (16)$$

The testing for the accuracy of predictions is based on the average squared forecast error, which is computed as

$MSE(z_{T+k}) = \hat{\gamma}_0 - \widetilde{\gamma}'_k V^{-1}\tilde{\gamma}_k$, where $\tilde{\gamma}_k = (\hat{\gamma}_{T+k-1},\ \hat{\gamma}_{T+k-2}, \dots ,\ \hat{\gamma}_k)$.

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,alarge value indicates a poor forecasting performance, whereas a value close to zero implies an almost-perfect forecast. We use threeaverage 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 may be interpreted as the percentage error, and has the advantage of being bounded from below by zero. Therefore, the lower the indicator the greater the model's forecast accuracy.Nevertheless, this loss function has drawbacks in any practical application. First, with zero values, we have a division by zero issue. Second, the MAPE does not have an upper limit. The AMAPE corrects almost completely the asymmetry problem between actual forecast values, and has the advantage of having both a zero lower bound and an upper bound. Like the MAPE, the smaller the AMAPE, the greater the accuracy of predictions made.

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

4. The Basic Empirical Results

4.1 Model Specification

Estimation results for the $\mathrm{ARFIMA}(p, d, q)$model are presented in Table 2. The best specification was chosen using the Schwartz Bayesian Information Criterion (BIC) andincludes one statistically-significant autoregressive terms of first order, one statistically-significant moving-average terms of seventh order as well as one structural break in 1946.

Global CO_2emissions are fractionally integrated with a statistically significant degree of persistence of d = 0.362. The confidence interval for the estimated fractional integration parameter is narrow, in the positive range,with an upper bound only marginally over 0.5. This means that, the series is better characterized as 'stationary but with long memory'. The effects of a one-time random shock in the innovations of these series are transitory, as the series are mean reverting. The effects of the one-time random shocks, however, will last longer than in the purely stationary case.

4.2 In-Sample Global CO_2 Emissions Forecasts

Figure 1 plots the actual valuesagainst the in-sample forecasts for globalCO_2emissions between 1900 and 2014(in-sample forecasts between 1750 and 1899 are available upon request). Table 3summarizes our forecasting accuracy analysis for the in-sample predictions. For the whole sample period, the mean absolute percentage error, MAPE, is 4.62% while the adjusted mean absolute percentage error, AMAPE, is 2.54%, indicating a good forecast performance. Moreover, only 9.73% of the predicted values lie outside the 95% confidence interval. In particular, 1.95% of the predicted values are above the upper limit while 7.78% are below the lower limit. In turn, the U-statistic shows a low level of inequality,suggesting that the forecasts compare very well with actual CO_2emissions. Moreover, the forecasts are unbiased and have small variance proportion. Accordingly, most of the forecast error,90.96%, can be attributed to the covariance component, i.e., the unsystematic forecasts error.

4.3 Out-of-SampleForecastsof Global CO_2 Emissions

Using data from 1751 to 2008 to estimate the ARFIMA model with one structural break in 1946, we forecast the remaining 5 observations until 2014. The results are shown in Figure2 and in Table4.The forecast is acceptable for the sub-sample, and only somewhat overestimates the emissions for 2009 and underestimatesCO_2emissions for 2010. For the remaining three years, the forecasts are fairly aligned with the CO_2emissions on record. The MAPE of the forecast is only 1.26%, and the same occurs when we correct the asymmetry problem between recorded and forecast values. Indeed, the AMAPE of the forecast is just 0.64%.The U-statistic, the bias proportion and the variance proportion are all small, indicating a very good forecast performance, with 95.91% of the bias concentrated on the unsystematic forecasts error.

5. Global CO_2Emissions Forecasts Until2100

5.1 The ARFIMA Forecasts

Having established a good forecasting performance of the statistical ARFIMA model in both in-sample and hangout sample forecasts, we use these estimates to forecast CO_2emissions until 2100. The results are shown in Figure 3 and in Table 5.CO_2emissions are projected to increase from 35,889Mtin 2014 to almost 48,689Mt in 2100. More specifically, the levels of CO_2emissions in 2030, 2040, 2050 and 2100, are forecasted to be about 23.1%, 29.1%, 33.7%, and 45.4% above the 2010 levels, respectively.

A notable feature of our forecast is that it suggests a continuous slowdown in the increase in the CO_2emissions. The ARFIMA framework seems to capture quite well the shift in the CO_2emissions pattern that actually occurred in the last decade due to more active environmental policies worldwide,as well as the more recent financial crisis and its economic aftershocks.

Despite this pattern, our projection suggests a reference path for global CO_2emissions which,unsurprisingly, does not meet the global CO_2emission goals designed to stabilize the concentration of CO_2 in the atmosphere at levels consistent with avoiding the most extreme outcomes of climate change.

5.2 Comparing the Updated Forecasts with the Previous Forecasts

As mentioned before, this paper updates the CO_2 emissions forecasts in Belbute and Pereira (2015) by considering more recent CO_2 emissions data just released and by accommodating structural breaks in the estimation of the basic ARFIMA model.

These updates result in a clear reduction of forecasted emissions. In fact, in this paper, we project updated 2030, 2040, 2050, and 2010 CO_2 reference emissions at about 23.1%, 29.1%, 33.7%, and 45.4%, above 2010 emission levels, respectively. In Belbute and Pereira (2015), the equivalent figures are about 27.4%, 34.4%, 39.8%, and 54.5% above 2010 levels, respectively.

5.3 Comparing the Forecasts with Other Available Reference Forecasts

Next, we comparethe updated forecasts with the reference forecasts used by different international organizations.To facilitate comparisons, we focus on projected reference changes at different points vis-à-vis the CO_2emission levels in 2010. IEA(2015) projects reference CO_2emissions in 2030 and 2050 at 39% and 48-55% above emission levels in 2010. In turn, OECD (2012) projects 2030, 2040, 2050 reference emissions about 32%, 58% and 70% above 2010. Finally, EIA (2014) projects 2030 and 2040 reference emissions at 33.5% and 42.9% above 2010 levels.

As a reminder, again,we project 2030, 2040, and 2050CO_2reference emissions at about 23.1%, 29.1%, and 33.7%,above 2010 emission levels, respectively. This suggests that we project a less pessimistic trend of CO_2emissions into the future. Furthermore, given the slowly declining pattern of marginal changes in CO_2emissions that we project, the difference between our reference case and the existing reference projections will tend to widen as we move further into the future.

5.4 Comparing Our Forecasts with Alternative Policy Scenarios for CO_2Emissions

The relevance of our lower reference case projections becomes apparent when we consider the paths for CO_2emissions projected under alternative policy scenarios or required to reach certain emission targets.

For example, the European Unionaims to achieve by 2030 areduction of CO_2emissions that is equivalent to 40% of 1990 emission levels [see, for example, EC (2014a), and (2014b)]. Translating this goal into a global objective would mean a reduction of about 9Mt by 2030, compared to the reference scenario.On the other hand, IEA(2015)'s INDC scenario aims at an 8% increase in 2030 versus 2013, or an increase of about 3Mt. Other scenariossuch as IEA (2015)'s Scenario 450 assume an actual reduction in emissions, while a bridge scenario postulates seriously curtailing emissions.

Under our reference forecast, the globalized EU emissions target would mean a reduction about the same size of the increase we project for 2030 compared to 2010, i.e. 8.97 Mt.In practice, this target would mean keeping emissions at the 2010 level, an effort worth a 23.1% reduction in emissions under our reference scenario, and between 32% and 39% under alternative reference scenarios**.**In turn, for the IEA (2015) INDC scenario's objectives, given our reference scenario, this would mean cutting projected additional CO_2emissions by an additional 33%.The point is that, with our lower projections of CO_2emissions, the ongoing policy goals are much more attainable.

6. Conclusions and Policy Implications

Our reference forecast suggests that CO_2emissions are clearly below the levels suggested by other reference scenarios available in the literature.This is important, as it suggests that the ongoing policy goals are actually much closer to reach than what is often implied by the standard CO_2reference emission scenarios. This is not to say that policy makers should rest on their laurels and relax theirongoing energy and environmental policy efforts to achieve such targets,but rather that whatever efforts are agreed upon will likely be more effective than what is implicit in the existing reference forecasts. In other words, the current CO_2emissions targets can be achieved at a much loweroverall cost than what is suggested by the conventional reference forecasts.

A possible reaction to the lower emissions path in the new reference scenario presented here could be that it is better to err on the side of caution – that is, it would be better to use the higher projected CO_2emissions as suggested by other reference forecasts. However, this situation reflects a delicate trade-off between two competing negotiation strategies. On one hand, there is a view that having higher emission reference forecasts increases the likelihood of decisive policy action and thus guarantees that the policies adopted will less likely undershoot the required objectives. On the other hand, there is also the view that, having lower and more realistic reference emissions projections gives a more accurate assessment of the policy efforts that are indeed required, and thus underscores the lower costs involved in mitigation efforts, thereby making all the more likely the adoption of more widespread energy and environmental policy efforts.

Finally, it should be mentioned that we see our new reference forecasts as a benchmark to be compared and contrasted with other reference forecasts generated by either univariate or more complex multivariate models. It ought to be a natural starting point to which other economic or demographic assumptions are to be added upon. Indeed, the evidence for long-term memory in CO_2emissions that we uncovered through our fractional integration approach suggests that transitory shocks will have temporary although long-lasting effects. Accordingly, in forecasting alternative and more elaborated policy scenarios, a more comprehensive multivariate approach should be pursued.

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

Decades	Total CO_2(Mt) annual average	Shares (%)				
		Solid Fuels	Liquid Fuels	Gas Fuels	Cement	Gas Flaring
1751 - 1759	10.992	100.00	-	-	-	-
1760 - 1769	10.992	100.00	-	-	-	-
1770 - 1779	14.290	100.00	-	-	-	-
1780 - 1789	17.954	100.00	-	-	-	-
1790 - 1799	22.717	100.00	-	-	-	-
1800 - 1809	34.075	100.00	-	-	-	-
1810 - 1819	44.334	100.00	-	-	-	-
1820 - 1829	59.723	100.00	-	-	-	-
1830 - 1839	95.997	100.00	-	-	-	-
1840 - 1849	149.491	100.00	-	-	-	-
1850 - 1859	248.419	100.00	-	-	-	-
1860 - 1869	420.261	99.74	0.26	-	-	-
1870 - 1879	664.283	99.34	0.77	-	-	-
1880 - 1889	1,021.890	98.03	1.54	0.50	-	-
1890 - 1899	1,499.309	96.80	2.64	0.54	-	-
1900 - 1909	2,411.645	95.81	3.52	0.68	-	-
1910 - 1919	3,210.763	93.85	5.15	1.00	-	-
1920 - 1929	3,569.835	86.25	11.81	1.74	0.21	-
1930 - 1939	3,812.758	79.01	17.10	2.95	0.92	-
1940 - 1949	4,919.653	73.91	20.97	4.30	0.82	-
1950 - 1959	7,390.654	59.82	29.91	7.40	1.40	1.47
1960 - 1969	11,292.448	46.27	39.30	10.76	1.87	1.81
1970 - 1979	17,153.382	35.63	47.23	12.93	2.10	2.12
1980 - 1989	20,083.850	39.63	41.85	15.09	2.43	1.01
1990 - 1999	23,368.992	37.51	40.87	18.08	2.95	0.58
2000 – 2014	30,772.292	39.82	36.34	18.62	4.53	0.69
Sample Averages						
1751-2014		83.04	21.86	7.95	2.22	1.23
1947-2014		44.50	38.17	13.60	2.57	1.23

Table 2 – Fractional Integration Results

Variable	Coefficient	Estimates	Std. Err.	95% Confidence interval	BIC
Global CO_2 emissions	α_1	0.838 (0.000)	**0.057**	[0.726 ; 0.951]	27.600
	θ_7	0.330 (0.000)	0.042	[0.247 ; 0.412]	
	t_{1946}	441,345 (0.000)	22,093	[398,044 ; 484,646]	
	d	**0.362 (0.000)**	**0.074**	**[0.216 ; 0.508]**	

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

Table 3– Five-Year In-Sample Forecasts for the Horizon1900 to 2014

Time	Actual	In-sample forecasts	Innovations		95% Confidence interval	
			Level	Percentage of the actual	Lower limit	Upper limit
1900	1,956.58	1,945.39	11.19	0.57	1,360.48	2,436.21
1905	2,429.23	2,354.07	75.16	3.09	1,778.92	2,852.24
1910	3,000.82	2,913.48	87.34	2.91	2,400.37	3,473.21
1915	3,070.43	3,056.00	14.44	0.47	2,419.18	3,502.12
1920	3,414.85	3,055.26	359.59	10.53	2,335.48	3,444.46
1925	3,572.40	3,461.44	110.96	3.11	2,930.32	4,032.06
1930	3,858.19	4,169.98	-311.79	-8.08	3,793.85	4,902.90
1935	3,762.93	3,601.53	161.40	4.29	3,082.82	4,217.35
1940	4,759.54	4,233.57	525.97	11.05	3,868.12	5,001.02
1945	4,250.24	4,824.33	-574.09	-13.51	4,365.16	5,511.50
1950	5,972.32	5,696.89	275.43	4.61	4,961.46	6,069.69
1955	7,481.89	7,313.25	168.64	2.25	6,582.17	7,698.33
1960	9,412.82	9,413.53	-0.71	-0.01	8,793.17	9,893.86
1965	11,468.32	11,447.27	21.05	0.18	10,863.72	11,956.56
1970	14,850.19	14,286.56	563.63	3.80	13,879.11	14,928.29
1975	16,839.74	17,355.39	-515.64	-3.06	16,863.49	17,892.91
1980	19,466.83	20,123.67	-656.84	-3.37	19,821.79	20,842.65
1985	19,924.83	19,992.07	-67.24	-0.34	19,211.31	20,357.95
1990	22,427.34	22,638.67	-211.33	-0.94	22,140.79	23,179.46
1995	23,354.34	23,888.48	-534.14	-2.29	22,915.67	24,145.90
2000	24,779.63	24,973.84	-194.21	-0.78	23,861.29	25,147.35
2005	29,590.46	28,959.78	630.69	2.13	28,615.73	29,657.51
2010	33,488.96	32,609.72	879.24	2.63	31,646.93	33,325.03
2014	35,889.65	35,944.82	-55.17	-0.15	34,184.00	37,546.74
Mean Absolute Percentage Error (MAPE)					4.62%	
Adjusted Mean Absolute Percentage Error (AMAPE)					2.54%	
Theil Inequality Coefficient					0.0125	
Mean Squared Error decomposition						
Bias proportion					0.0814	
Variance proportion					0.0091	
Covariance proportion					0.9096	

Figure 1- In-Sample ARFIMA Predictions for 1900-2014

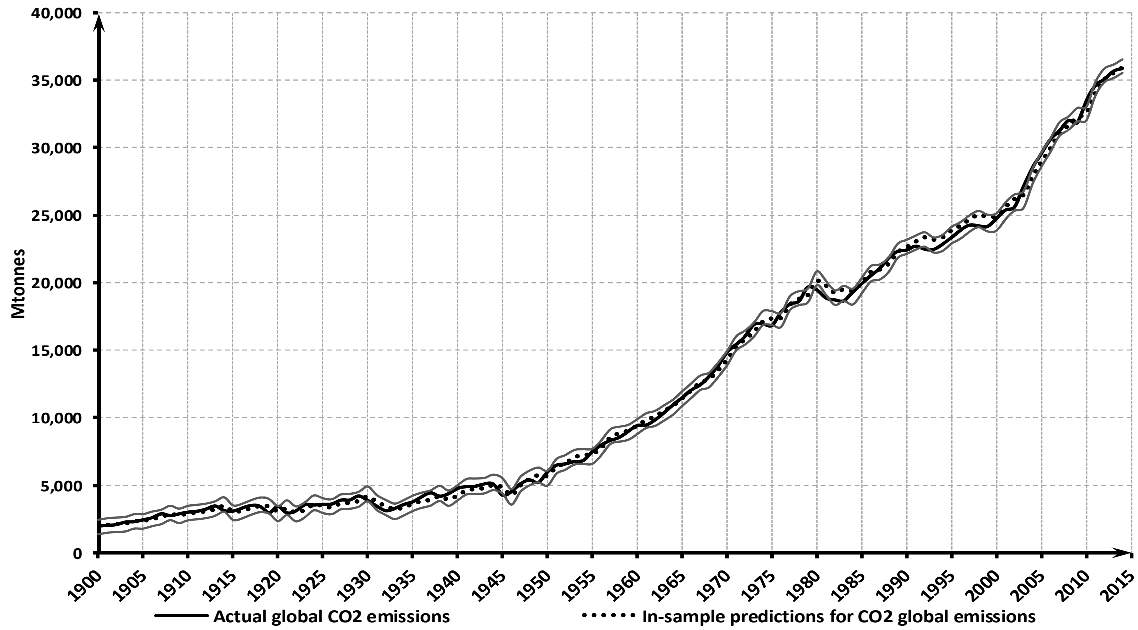

Table 4 –Forecasts and Actual CO_2Emissions for the Hangout Sample: 2009-2014

Time	Actual	In-sample forecasts	Innovations		95% Confidence interval	
			Level	Percentage of the actual	Lower limit	Upper limit
2009	31,876.80	32,268.64	-391.84	-1.23	31,556.79	32,984.72
2010	33,488.96	32,609.72	879.24	2.63	31,646.63	33,325.03
2011	34,621.14	34,059.34	561.80	1.62	32,950.88	34,883.84
2012	35,082.89	35,069.43	13.47	0.04	33,703.11	36,136.17
2013	35,669.16	35,546.34	122.82	0.34	33,945.90	368,48.23
2014	35,889.65	35,944.82	-55.17	-0.15	34,184.00	37,546.74
Mean Absolute Percentage Error (MAPE)					1.26%	
Adjusted Mean Absolute Percentage Error (AMAPE)					0.64%	
Theil Inequality Coefficient					0.0158	
Mean Squared Error decomposition						
Bias proportion					0.0299	
Variance proportion					0.0110	
Covariance proportion					0.9510	

Figure 2–Forecastsand Actual CO_2Emissions for the Hangout Sample: 2009-2014

Table 5 –Global CO_2Emissions Forecasts for 2015-2100

Years	Total CO_2 emissions (forecasts - f_t)	RMSE		95% Confidence interval	
		$MtCO_2$	$RMSE_t/f_t$ (%)	Lower limit	Upper limit
2015	36,559.6	397.5	1.1	35,905.7	37,213.4
2020	38,476.7	1,091.2	2.8	36,681.9	40,271.5
2025	39,968.0	1,923.2	4.8	36,804.6	43,131.4
2030	41,226.0	2,709.8	6.6	36,768.7	45,683.2
2035	42,302.2	3,448.0	8.2	36,630.7	47,973.7
2040	43,235.8	4,148.3	9.6	36,412.5	50,059.1
2045	44,053.7	4,817.5	10.9	36,129.5	51,977.8
2050	44,772.8	5,460.4	12.2	35,791.2	53,754.4
2055	45,409.8	6,080.2	13.4	35,408.7	55,410.8
2060	45,974.7	6,679.4	14.5	34,988.1	56,961.3
2065	46,475.1	7,259.8	15.6	34,533.8	58,416.5
2070	46,919.5	7,823.1	16.7	34,051.6	59,787.4
2075	47,315.7	8,370.5	17.7	33,547.5	61,083.9
2080	47,663.7	8,902.9	18.7	33,019.7	62,307.7
2085	47,976.7	9,421.5	19.6	32,479.8	63,473.6
2090	48,249.5	9,926.8	20.6	31,921.3	64,577.6
2095	48,483.5	10,419.7	21.5	31,344.6	65,622.3
2100	48,685.2	10,900.7	22.4	30,755.2	66,615.2

Figure 3–Global CO_2 Emissions Forecasts from 2015 until 2100