Do Global CO_2 Emissions from Fuel Consumption Exhibit Long Memory? A Fractional Integration Analysis

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Abstract

In this paper we use an ARFIMA approach to measure the degree of fractional integration of aggregate world CO_2 emissions and its five components – coal, oil, gas, cement, and gas flaring. We find that all variables are stationary and mean reverting, but exhibit long-term memory. With aggregate CO_2 emissions as a reference, our results suggest that both coal and oil combustion emissions have the weakest degree of long-range dependence, while emissions from gas, and gas flaring have the strongest. With evidence of long memory, we conclude that transitory policy shocks are likely to have long-lasting effects. Although the effects of any active policy on CO_2 emissions take longer to disappear, they preserve their temporary nature. Accordingly, permanent effects on CO_2 emissions require a more permanent policy stance. In this context, if one were to rely only on testing for stationarity and non-stationarity, one would likely conclude in favor of non-stationarity, and therefore that even transitory policy shocks have permanent effects. Our fractional integration analysis highlights that this is not the case.

Keywords: CO2 emissions, Long memory, ARFIMA model.
JEL Codes: C22, O13, Q41.

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1. Introduction

Growing concerns about CO_2 emissions and climate change have focused the attention of academics and policy makers all over the world on just how effective energy and environmental policies are. In this setting, understanding the persistence in CO_2 emissions is a matter of immediate policy relevance. At the core of the renewed policy focus is the idea that public policy for a green economy should extend well beyond the usual "getting prices right" recommendation, in order to nudge both consumption and production patterns towards a more sustainable path of CO_2 emissions [see, for example, EC (2013, 2014a, 2014b), Parry et al (2014), Tietenberg and Lewis (2014), IMF (2014), OECD (2015), and USEIA (2014)].

Measuring the persistence of CO_2 emissions is crucial for the design, implementation, and effectiveness of both energy and environmental policies aimed at lowering the economy's addiction to carbon. If CO_2 emissions are in fact stationary, then transitory public policies (i.e., those that promote energy efficiency, fuel switching or lower emissions from transportation) will tend to have only transitory effects. Permanent changes, therefore, require a more permanent policy stance. On the other hand, if CO_2 emissions are non-stationary, then even transitory policies will have permanent effects on emissions and a steady policy stance is less critical.

The literature on the degree of persistence in CO_2 emissions has mostly concentrated on testing for the presence of unit roots, which in turn is motivated by the focus on identifying the long-term relationship between CO_2 emissions and the use of energy or even GDP [see, among others, Galeotti et al. (2006), Richmond and Kaufman (2006), Akbostancı et al. (2009), Aslanidis (2009), Fodha and Zaghdoud (2010), Jaunky (2011), and Magazzino (2014)]. The main result of these studies is that carbon emissions and GDP, energy use or income are non-stationary – i.e., integrated of order one – although not always co-integrated. Traditional autoregressive univariate unit root tests, however, are limited to the stationary/non-stationary dichotomy. The unit root tests only provide evidence on the existence or absence of a permanent component, but not on how big it is. That is, the unit root test only confirms that the current value of a variable is determined by its past behavior, and is unable to identify how far back in time that influence extends.

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, for example, Palma (2007)] This long range dependence is characterized by a hyperbolically-decaying autocovariance function, and by a spectral density that approaches infinity as the frequency tends to zero. The intensity of this phenomena can be measured by a differencing parameter "d", which includes the stationary case ($d = 0$) and the non-stationary case ($d = 1$) as the two extreme cases. When $d < 1$ the process is mean reverting. For $0.5 < d < 1$, the process is not covariance stationary, although it is mean reverting. When $-0.5 < d < 0.5$ the process is said to be covariance stationary and ergodic with a bounded and positively valued spectrum at all frequencies. When $-0.5 < d < 0$, the process has intermediate memory. In turn, when $0 < d < 0.5$, the process is stationary, but displays long memory in the sense that its autocorrelation function decays exponentially, rather than geometrically as in the case of short memory ($d = 0$). Long memory implies a significant dependence between observations widely separated in time, and therefore the effects caused by shocks tend to decay only slowly, although they still are mean-reverting in nature.

While this more flexible approach has been widely adopted in the macroeconomics literature, only more recently has the presence of long-range dependence also been tested in the literature on energy [see, for example, Elder and Serletis (2008), Lean and Smyth (2009), Gil-Alana et al. (2010), Apergis and Tsoumas (2011, 2012), and Barros et al. (2012a, 2012b)]. The results from these fractional integration tests generally suggest that the energy variables considered – production, final demand, prices – all exhibit long-term memory.

More directly relevant from our standpoint, there is now a budding literature considering the possibility that CO_2 emissions released to the atmosphere may follow a long memory process [see, for example, Barassi et al. (2011), Liu and Chen (2013) and Gil-Alana et al. (2015)]. The evidence so far is that in many cases the existence of unit roots cannot be rejected, and, in other cases, emissions are non-stationary, but mean reverting. Overall, the evidence seems to go in the direction of very long memory. In no case have global CO_2 emissions or their different sources been considered in the literature.

In this article we contribute to the literature on the long-memory properties of global CO_2 emissions by measuring their degree of fractional integration. We use data on worldwide CO_2 emissions from the onset of the Industrial Revolution, i.e., from 1750 onwards. We consider not only the degree of persistence in aggregate CO_2 emissions but also each of its main sources – solid fuels, liquid fuels, gas fuels, cement production, and gas flaring.

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

The remainder of this article is organized as follows. Section 2 presents the data set. Section 3 provides a brief technical description of the methodology used, and Section 4 discusses the empirical findings. Finally, Section 5 provides a summary of the results, and discusses their energy and environmental policy implications.

2. Data: sources and description

In this paper we use annual data for the world's overall CO_2 emissions from fossil-fuel consumption covering 1751 to 2013. Data were obtained from the Carbon Dioxide

Information Analysis Centre [see Boden et al. (2013)]. 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 3.667, the ratio of the two atomic weights. See Joint Research Centre of the European Commission (2014) for a detailed comparison among different available measurements of CO_2 emissions.

The first column of Table 1 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 1750, CO_2 emissions were mostly stable over time, and caused by the release of carbon into the atmosphere from deforestation and land-use activities [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 36,131 Mt in 2013. The average rate of growth for the whole-period sample was 3.08% per year. For the more recent period from 2000 to 2013, the annual growth rate was slightly lower, at 2.7%.

This aggregate increase in CO_2 emissions hides a variety of important trends throughout the sample period. During the period of the first industrial revolution, i.e., between 1750 and the 1830s, total CO_2 emissions remained 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 to the present day.

During the period 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 83.86% of CO_2 emissions. When considering only the period following World War II, coal accounted for 42.95% of all CO_2 emissions. Having reached a trough in 1974 representing 34.16% of all emissions, it rose again to 42.98% in 2013.

CO_2 emissions from oil combustion started in the 1860s, and after 1920 became a significant source of energy. It represents 11.56% of the worlds' 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 39.48% of all emissions. In 2013, the CO_2 emissions from liquid fuel consumption accounted for 37.73% of total emissions.

Gas fuel consumption includes both liquefied petroleum gas and more recently, natural gas. It is responsible for 3.63% 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 13.80% of all emissions. It reached a peak in 1999 with 19.21%, but after that date it has remained relatively stable. In 2013 it accounted for 18.56% of emissions.

Finally, CO_2 emissions from cement production and gas flaring are more residual. They account for a combined amount of around 0.95% 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 2.48% and 1.28%, of total emissions, respectively.

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) nor 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, Palma (2007)].

A time series $x_t = y_t - \beta z_t$ – where β is the vector of coefficients, z_t represents all deterministic factors of the process, y_t, and $t = 1, 2, \dots n$ – 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, 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:

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

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 decay exponentially. More formally,

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

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

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

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 $\approx$ means that the ratio between the two sides of (7) will tend to unity as $\lambda \to 0^+$.

In general, the larger the value for the fractional-difference parameter d, the greater the degree of persistence. Specifically, we have several cases.

If $-0.5 < d < 0$, then the autocorrelation function decays at a slower hyperbolic rate but the process is called anti-persistent or, alternatively, is said to have a rebounding behavior or negative correlation, because the autocorrelations for lags greater than zero are negative.

If $0 < d < 0.5$, the process x_t reverts to its mean, but the auto-covariance function decreases very slowly and hyperbolically as a result of the strong dependence on past values. The spectral density function is unbounded at the origin and x_t is said to exhibit long-memory behavior. This means that the effects of a random shock in the innovations of the series are transitory and the series will eventually revert to its mean. Nevertheless, the effects will last longer than in the purely stationary case $(d = 0)$.

If $0.5 < d < 1$, the process becomes more non-stationary in the sense that the variance of the partial sums (5) increases, but the series retains its mean-reverting property.

Finally, if $d > 1$, the process is non-stationary and non-mean-reverting, i.e. the effects of random shocks are permanent.

3.2 ARFIMA processes

An auto-regressive 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 by either 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 becomes

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

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

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

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

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

The estimation of the parameters of the ARFIMA model is done using maximum likelihood. The log Gaussian likelihood was established by Sowell (1992) and is

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

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 $j = 1, 2, \dots\ t-1$ and $t = 1, 2, \dots\ T$.

4. The Empirical Results

4.1 Standard Unit Roots Tests

As a point of reference, we begin by considering the results from the standard unit roots tests, i.e., the tests that only consider the dichotomy between stationarity and non-stationarity. The results are traditionally interpreted as suggesting that the effects of one-time shocks to the series are either transitory, if the series is stationary, or permanent if the series is not stationary. We use the Augmented Dickey-Fuller (ADF) t-test to test the null hypothesis of a unit root in aggregate CO_2 emissions and its components in log differences. We used the Schwartz Bayesian Information Criterion (BIC) as the model selection criteria.

Our results are presented in Table 2 and suggest that all series under consideration are non-stationary but stationary in first differences, that is, they are I(1). Based on these test results we can conclude that one-time shocks to all of these series have permanent effects. This means that the one-off policy shocks have permanent effects and that maintaining a steady policy stance is not critical, since even one-time shocks will lead to permanent effects. In addition, there is nothing we can say based on these results on the relative degree of persistence of the different components of the global CO_2 emissions.

It is also interesting to note that these results coincide with the directly-related literature on stationarity/non-stationarity in CO_2 emissions to confirm the presence of unit roots. Furthermore, even the little evidence using a fractional integration approach suggests that unit roots are prevalent. In Barassi et al. (2011), CO_2 emissions in five of the 18 OECD countries considered – Australia Canada, Denmark, UK and US – display unit roots. In turn, in Gil-Alana et al. (2015), CO_2 emissions in two of the four major emitting economies – China and India – display unit roots.

4.2 Fractional integration – 1750-2013

In this section and the next one, we present the main estimation results of the different $\mathrm{ARFIMA}(p, d, q)$ models using natural logarithms of the raw data. In all cases, we present the estimation results of the auto-regressive and moving average components, if present, as well as of the estimated fractional integration parameter d. We used the Schwartz Bayesian Information Criterion (BIC) as the model selection criteria. For each estimated parameter we present the corresponding standard errors, p-values and 95% confidence intervals.

Estimation results for the whole sample period from 1750 to 2013 are presented in Table 3. Empirical results suggest that there is statistically-significant evidence for the non-rejection of the presence of long memory for both aggregate CO_2 emissions as well as its five different components.

Examining the results in more detail, we find that all the estimates of the fractional parameter d are between 0 and 1, thus allowing us to reject both the case of pure stationarity ($d = 0$) and the unit root model ($d = 1$). More specifically, all estimated parameters d are statistically significant at the 1% level, and lie within the interval (0, 0.5). Total emissions have a degree of persistence of d = 0.354, and emission from gas and gas flares show the highest degrees of persistence ($d =$ 0.467 and d = 0.438), while emissions from coal show the least persistence ($d =$ 0.271). In turn, emissions from oil and cement have degrees of persistence close to the aggregate ($d =$ 0.303 and d = 0.368, respectively).

Overall, these results mean that the different series are better characterized as being 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. A steady policy stance is thus necessary to yield a permanent impact. The effects of the one-time random shocks, however, will last longer than in the purely stationary case. These series exhibit long-memory behavior. Accordingly, a permanent policy stance will tend have cumulative effects over time.

The confidence intervals for the estimated fractional integration parameters are relatively narrow and always in the positive range. Also, for aggregate emissions as well as emissions from coal and oil the upper bounds are lower than 0.5, thus reinforcing the idea that emissions are stationary and mean-reverting, but exhibiting long term memory. For emissions from gas, cement, and gas flaring, however, the upper bounds are greater than 0.5, leaving open the possibility that these series may be non-stationary, though mean-reverting.

These results pointing to stationarity, but with long memory, are very much in line with recent evidence on the levels of persistence in energy demand and production [see, for example, Lean and Smyth (2009), Gil-Alana, et al. (2010), Apergis and Tsoumas (2011, 2012), and Barros et al. (2012a)]. This is relevant as CO_2 emissions bear a direct technical relationship with energy consumption.

More importantly, however, our results are different in important ways from the evidence in the literature on CO_2 emissions. Our results of stationarity with long memory coincide with the evidence in Barassi et al. (2011) for the period 1870-2004 for only four of the 18 OECD countries studied – Finland, Germany, Netherlands, and Norway. For three other countries – Belgium, France, and Sweden - CO_2 emissions are found to be non-stationary, but mean reverting, the same being likely true for six other countries – Australia, Italy, Japan, Portugal, Spain, and Switzerland. Furthermore, Gil-Alana et al. (2015) present evidence for 1751-2012 for non-stationarity with mean reversion for UK and US. It is worth recalling that in the remaining cases in both papers the authors identify unit roots. Accordingly, we find that, at the global level, both aggregate CO_2 emissions and CO_2 emissions from different sources show much shorter long-memory patterns than in these contributions to the literature.

4.3 Fractional integration – 1950-2013

We now re-consider the empirical evidence considering a much smaller sample, 1950-2013. Indeed, we saw that after World War II there were important changes in the evolution of CO_2 emissions – emissions from oil are now very significant, and emissions from gas have established themselves as an important source of emissions. Furthermore, and from a more intuitive perspective, this period may reflect more accurately the current persistence patterns in CO_2 emissions. Besides, we want to ascertain whether or not some of the differences vis-à-vis the literature may be sensitive to the sample being considered. Naturally, for some of the components of global emissions, i.e., cement and gas flaring, given the actual sample sizes, the results are either close to or very similar to the results found before. Estimation results for the period 1950-2013 are presented in Table 3.

Again, all of the estimates of the fractional parameter d are in the range $(0, 1)$, thus allowing us to reject both the pure stationary case ($d = 0$) and the unit root model ($d = 1$). Again, all series exhibit long-term memory as all estimated parameters d are statistically significant at 1% and lie within the interval (0, 0.5). Total emissions for this restricted period have a degree of persistence of d = 0.391, close to the 0.354 for the whole period. Emission from gas and gas flares show the highest degrees of persistence ($d =$ 0.464 and d = 0.438). In turn, emissions from oil and cement have degrees of persistence close to the aggregate ($d =$ 0.303 and d = 0.368). For all of these the results are rather close to the results with the whole sample.

The most important difference refers to the level of persistence for coal, which is now substantially larger than for the longer sample period ($d =$ 0.449 versus d = 0.271). This is quite understandable, since this was a time when emissions from coal became much less relevant in relative terms than before.

Finally, and as before, the confidence intervals for the estimated fractional integration parameters are relatively narrow and always in the positive range. Not surprisingly, however, with a much shorter sample period, the precision of our estimates is somewhat reduced, and the confidence intervals we obtain for our estimates are clearly wider than when the whole data set is considered. Now, only for emissions induced by oil combustion is the upper bound lower than 0.5. For aggregate emissions, as well as for emissions from coal, gas, cement, and gas flaring, the upper bounds are greater than 0.5, leaving open the possibility that these series may be non-stationary, though mean-reverting. In general this suggests an even longer memory than when the whole sample is considered.

4.4 Impulse response function analysis

We now consider the impulse response function analysis associated with the estimates for the whole period, 1750-2013. We focus on the duration and size of transitory shocks, ultimately determining what long-memory means in practical terms. Using the whole structure of the estimated ARFIMA stochastic process provides a more informative view than just considering the fractional integration parameters alone. (Results for the shorter period, 1950-2013, are not substantially different, and are available upon request.) The accumulated impulse response functions and their 95% upper and lower limits (the dashed lines) for a century are presented in Figures 1 through 6.

Considering first the impulse response function at the aggregate level, we find that a one-time shock of 1 Mt in CO_2 emissions in 2014 accumulates into a total increase in emissions over time of 6.38 Mt through the feedback mechanisms of the stochastic process. Of this total, 50% accrues within the first 11 years, and 75% within the first 29 years. The bulk of these effects appear within a 68 year period. So we observe that although the pattern of the effects is front loaded, progressively decreasing marginal effects persist for quite a while, giving a good sense of what long memory means in practical terms.

The same pattern of fast appearing effects followed by a slow marginal decay of the effects appears with the three fossil fuel sources of CO_2 emissions. Specifically, a one-time shock of 1 Mt in emissions from solid, liquid and gas fossil fuels translates into a long-term increase in accumulated emissions of 4.83 Mt, 2.96 Mt, and 5.80 Mt respectively. Convergence is faster for emissions from solid and liquid fossil fuels as 50% appear within 8 and 3 years, respectively, while 95% are observed within 49 and 36 years respectively. The opposite is true with respect to emissions from gas. The long-term effect is 5.80Mt. Of this effect, it takes 15 years to reach half of this effect and 75 years to reach 95%.

The patterns of response to 1 Mt one-time shocks in CO_2 emissions from cement and gas flaring are different. They accumulate up to a certain point, but then the process reverses, so that the accumulated effects peak early in the time horizon. The total accumulated effects of shocks to emissions in cement reach 8.23 Mt, and peak by year 46 at 14.10 Mt. In turn, the accumulated effects of a shock in CO_2 emissions from gas flaring is 0.38 Mt, and peak after 8 years at 1.28Mt, followed by a long period of a rather slow decline in emissions. We still see a strong pattern of rather long memory.

5. Conclusions and Policy Implications

This article tests for the presence of long memory in the world's CO_2 emissions from fuel-fossil combustion, including cement production. Our findings suggest that the presence of long memory in the world total CO_2 emissions cannot be rejected, both for aggregate CO_2 emissions and for each of its five components – coal, petroleum, gas, cement, and gas flaring.

Specifically, all of the estimated fractional-integration parameters are positive and smaller than 0.5. Therefore, we reject both the purely stationary case ($d = 0$) as well as the unit root case ($d = 1$). All variables are stationary and mean reverting, but with autocorrelations decaying at a hyperbolic rate. In some cases, the upper limit of the confidence intervals for the fractional-difference parameter d is greater than 0.5, suggesting that the series might be non-stationary, but still mean reverting. At any rate, the effects of a given random shock will be transitory, but reverting back to their trend at a slower rate than in the purely-stationary case ($d = 0$). Accordingly, we find strong evidence of a significant dependence between CO_2 emissions widely separated in time, i.e., CO_2 emissions exhibit long-term memory.

Using our estimate of the fractional integration parameter for aggregate CO_2 emissions as a reference point, our results suggest that the emissions from coal and oil combustion exhibit the weakest degree of long range dependence, while emissions from coal, gas, and gas flaring have the strongest levels of persistence. The degree of persistence for emissions from cement production is around average.

We further probe the characteristics of the different series in their response to transitory shocks by considering the accumulated impulse response functions. We show that for both aggregate CO_2 emissions and emissions from fossil fuel combustion, there is a strong pattern of front loading with half of the effects appearing with 8, 3, and 15 years, for solid, liquid and gas fossil fuels respectively. The bulk of the accumulated effects, however, takes 49, 36, and 75 years to appear, respectively.

Our findings on the long memory nature of CO_2 emissions have important implications for both the design and the effectiveness of energy and environmental policies. When CO_2 emissions are a purely-stationary process, that is, when they are a short memory process, then, in the wake of a policy shock, these emissions will tend to move away from and revert to their trend more quickly than in presence of long memory, that is, they will exhibit a strong dependence on past values. Given the existence of long memory, positive policy shocks (for instance, in the form of improving energy efficiency programs, subsidies for alternative energy sources, or CO_2 mitigation policies among others) are likely to be more effective as they are long lasting.

Despite the fact that the effects of any active policy on CO_2 emissions tend to disappear only slowly, they preserve their temporary nature. Accordingly, permanent effects on CO_2 emissions will require a more permanent policy stance. In this context, it is important to mention that, if one were to only rely on testing for the dichotomy between stationarity and non-stationarity, one would likely conclude in favor of non-stationarity and, therefore, even transitory policy shocks would seem to have permanent effects. Our fractional integration analysis highlights that this is not the case. The effects of transitory shocks are temporary, although long lasting.

These results also have important implications from a more technical perspective. In particular, they suggest the importance of accounting for the interactions of CO_2 emissions with energy, the economy, and climate both in terms of modeling and forecasting, as there is evidence that transitory shocks in CO_2 emissions exhibit long memory. Indeed, given the strong connection of the energy and transport sectors to the rest of the economy, the effect of energy policies may be transmitted to other sectors and even have impacts on the real economy, such as employment and output, feeding back CO_2 emissions.

Finally, it should be mentioned that the patterns of long memory we identified at the global level are nevertheless shorter than are usually thought [see Barassi (2011) and Gil-Alana et al. (2015)]. Our pattern of stationarity with long memory seems to be the exception in the literature and not the rule. In this sense, our argument for more permanent environmental policies is even more critical. This consideration also leads to an important avenue for further investigation. Indeed, it would be important to consider the issue of long-term memory at the national level for a large number of countries and CO_2 emission sources. This would allow us to identify the countries and in each country the national emissions sources, for which CO_2 emissions patterns are more persistent and for which, therefore, policies will likely be more effective.

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Table 1 – World total CO_2 emissions from fossil fuel consumption and cement production

Decades	Total CO2 (Mt) annual average	Shares (%)				
		Solid Fuels	Liquid Fuels	Gas Fuels	Cement	Gas Flaring
1750 - 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 - 2013	30,520.275	38.89	37.73	18.56	4.11	0.71
Sample Averages						
1750-2013		83.86	11.56	3.65	0.65	0.30
1950-2013		42.96	39.48	13.80	2.48	1.28

Table 2 – Traditional unit root results for emissions in log differences

Sample period: 1750-2013	Period	DET	Lags	t	ρ	p-value		BIC
Total emissions	1751-2013	None	6	2.495	0.748	0.012	**	-680.409
Solid fuels	1751-2013	none	6	-2.836	0.689	0.004	***	-675.459
Liquid fuels	1870-2013	Constant	1	-6.867	0.162	0.000	***	-298.468
Gas fuels	1885-2013	Constant	0	-11.098	0.132	0.000	***	-293.336
cement	1928-2013	Constant	0	-5.939	0.400	0.000	***	-177.32
Gas flaring	1950-2013	None	2	-2.538	0.541	0.011	**	-94.8235
Sample period: 1950-2013								
Total emissions		Constant	0	-5.217	0.380	0.000	***	-246.454
Solid fuels		Constant	0	-5.536	0.334	0.000	***	-244.054
Liquid fuels		Constant and trend	0	-6.016	0.257	0.000	***	-216.858
Gas fuels		Constant and trend	0	-7.942	0.075	0.000	***	-250.19
Cement		Constant and trend	0	-5.028	0.415	0.001	***	-234.431
Gas flaring		None	2	-2.538	0.541	0.011	**	-94.8235

Table 3 – Fractional Integration Results – 1750-2013

Variable	Sample period	Coefficient	Estimates	Std. Err.	p-value	*Conf. Interval (95%)*	MBIC
Total CO_2 emissions from fossil fuel consumption	**1751 - 2013**	α_1	0.444	0.110	*0.000*	[0.228 ; 0.629]	*2890.312*
		α_2	0.552	*0.109*	*0.000*	[0.339 ; 0.768]	
		θ_1	0.742	*0.082*	*0.000*	[0.582 ; 0.903]	
		θ_7	0.162	0.020	*0.001*	[0.065 ; 0.260]	
		d	**0.354**	**0.046**	***0.000***	**[0.263 ; 0.444]**	
CO2 emissions from solid fuel consumption	**1751 - 2013**	α_1	1.103	0.100	*0.000*	[0.906 ; 1.299]	*2721.582*
		α_2	-0.106	*0.099*	*0.285*	[-0.299 ; 0.088]	
		θ_7	0.370	*0.062*	*0.000*	[0.249 ; 0.492]	
		d	**0.271**	**0.076**	***0.000***	**[0.121 ; 0.420]**	
CO2 emissions from liquid fuel consumption	**1870 - 2013**	α_1	0.995	0.006	*0.000*	[0.984 ; 1.006]	*1506.227*
		d	**0.303**	***0.059***	***0.000***	**[0.186 ; 0.419]**	
CO_2 emissions from gas fuel consumption	**1885 - 2013**	α_1	0.406	0.102	*0.000*	[0.207 ; 0.605]	*1084.689*
		α_2	0.589	*0.101*	*0.000*	[0.390 ; 0.788]	
		θ_8	0.236	*0.098*	*0.016*	[0.044 ; 0.429]	
		d	**0.467**	**0.036**	***0.000***	**[0.395 ; 0.538]**	
CO2 emissions from cement consumption	**1928 - 2013**	α_1	1.122	0.018	*0.000*	[1.087 ; 1.157]	*512.337*
		α_8	-0.127	*0.017*	*0.000*	[-0.160 ; -0.094]	
		d	**0.368**	***0.097***	***0.000***	**[0.178 ; 0.557]**	
CO2 emissions from gas flaring consumption	**1950 - 2013**	α_1	0.666	*0.143*	0.000	[0.385 ; 0.948]	*514.467*
		α_3	*0.216*	*0.114*	0.059	[-0.008 ; 0.439]	
		d	***0.438***	***0.088***	**0.000**	**[0.255 ; 0.609]**	

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.

Table 4 – Fractional Integration Results – 1950-2013

Variable	Sample period	Coefficient	Estimates	Std. Err.	p-value	*Conf. Interval (95%)*	BIC
Total CO_2 emissions from fossil fuel consumption	**1950 - 2008**	α_1	1.169	0.179	*0.000*	[0.818 ; 1.521]	*741.998*
		α_2	-0.175	*0.177*	*0.321*	[-0.522 ; 0.171]	
		d	**0.391**	**0.109**	***0.000***	**[0.177 ; 0.605]**	
CO_2 emissions from solid fuel consumption	**1950 - 2013**	α_1	0.990	0.100	*0.000*	[0.969 ; 1.011]	*894.631*
		θ_{12}	-0.155	*0.132*	*0.241*	[-0.414 ; 0.104]	
		d	**0.449**	**0.058**	***0.000***	**[0.336 ; 0.564]**	
CO_2 emissions from liquid fuel consumption	**1950 - 2013**	α_1	0.992	0.010	*0.000*	[0.973 ; 1.011]	*909.411*
		d	**0.303**	***0.086***	***0.000***	**[0.134 ; 0.473]**	
CO_2 emissions from gas fuel consumption	**1950 - 2013**	α_1	0.549	0.120	*0.000*	[0.313 ; 0.785]	*774.641*
		α_2	0.447	*0.120*	*0.000*	[0.211 ; 0.682]	
		d	**0.443**	**0.057**	***0.000***	**[0.331 ; 0.554]**	
CO_2 emissions from cement consumption	**1950 - 2013**	α_1	0.992	0.008	*0.000*	[0.977 ; 1.008]	*607.619*
		θ_1	0.312	*0.118*	*0.008*	[0.081 ; 0.542]	
		d	**0.464**	***0.044***	***0.000***	**[0.377 ; 0.551]**	
CO_2 emissions from gas flaring consumption	**1950 - 2013**	α_1	0.666	*0.0143*	0.000	[0.385 ; 0.948]	*514.467*
		α_3	*0.216*	*0.114*	0.059	[-0.008 ; 0439]	
		d	***0.438***	***0.088***	**0.000**	**[0.255 ; 0.609]**	

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.

Figure 1: Cumulative IRF - aggregate CO_2 emissions

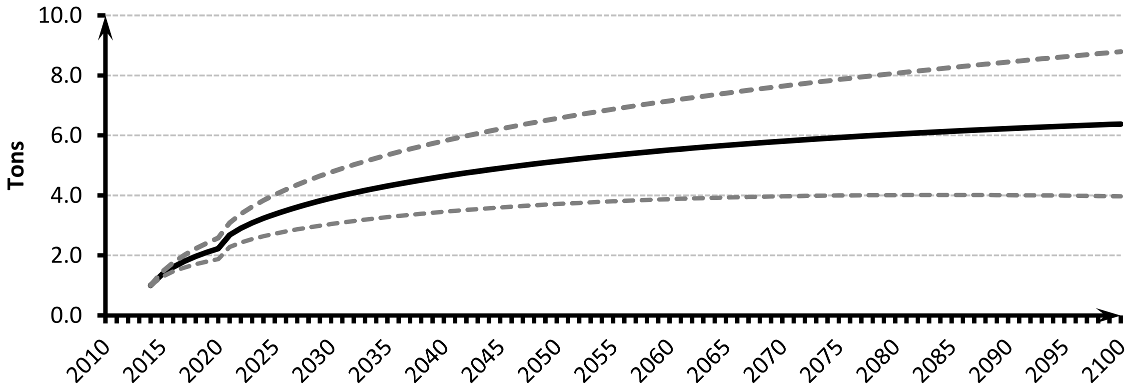

Figure 2: Cumulative IRF - CO_2 emissions from solid fossil fuels

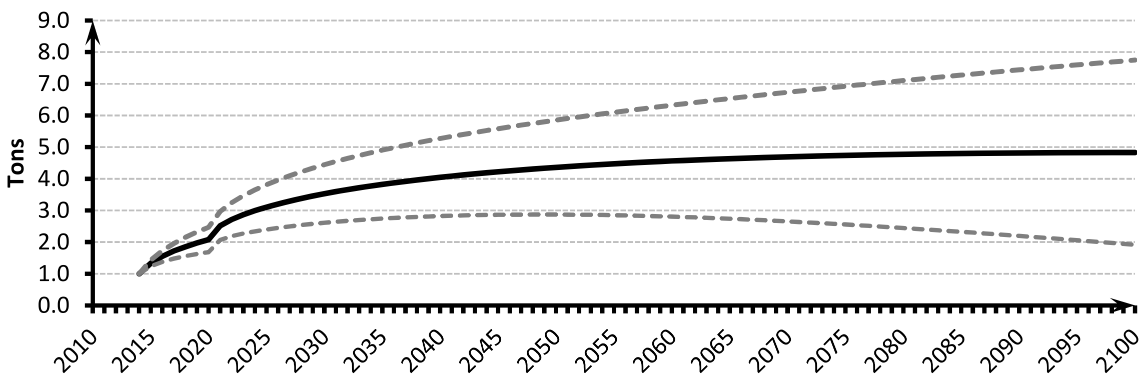

Figure 3: Cumulative IRF - CO_2 emissions from liquid fossil fuels

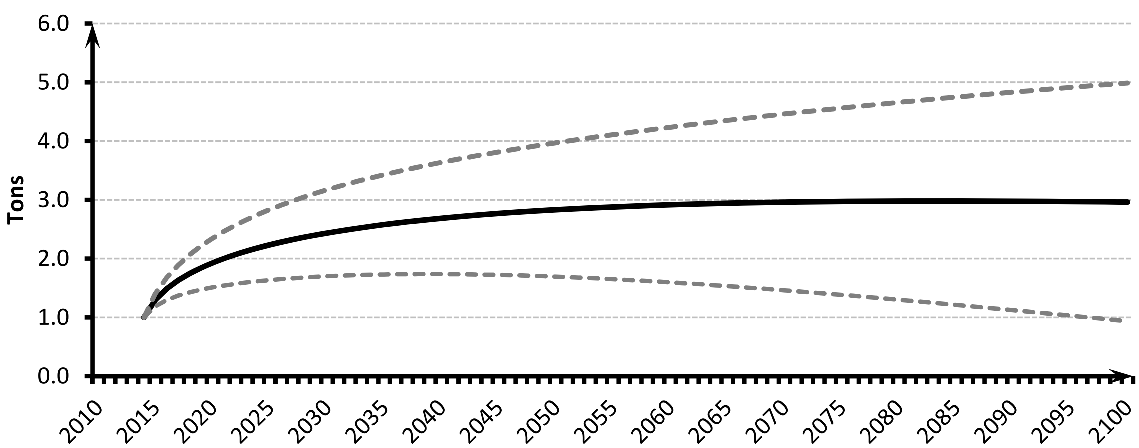

Figure 4: Cumulative IRF - CO_2 emissions from gas fossil fuels

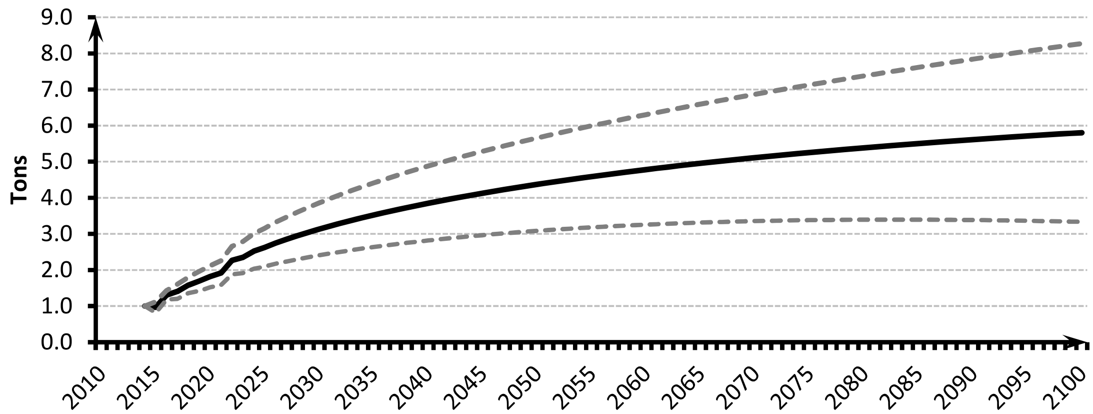

Figure 5: Cumulative IRF - CO_2 emissions from cement

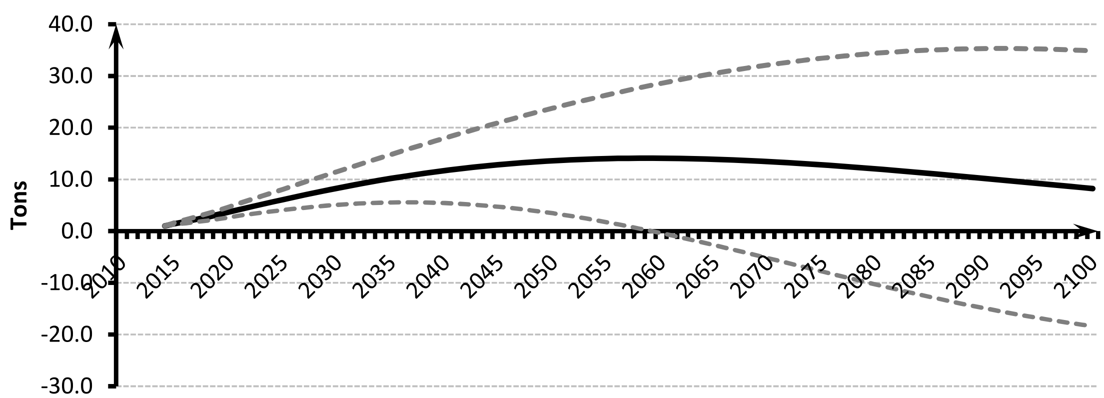

Figure 6: Cumulative IRF - CO_2 emissions from gas flaring