



Modeling persistence of carbon emission allowance prices[☆]



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ABSTRACT

This study reexamines the issue of persistence in carbon emission allowance spot prices, using daily data, and covering the period from 28/2/2007 to 14/05/2014. For this purpose we use techniques based on the concept of long memory accounting for structural breaks and non-linearities in the data, with both of these aspects potentially affecting the degree of persistence. Our results indicate that, while there is no evidence of non-linearity, when allowing for structural breaks, persistence of shocks to the carbon emission allowance is markedly reduced, with the same being transitory in nature for recent sub-samples.

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1. Introduction

Modeling and explaining CO₂ dynamics have received a great deal of attention in recent years related to an increase in greenhouse gases and climate change. Some recent studies have focused on the efficiency of carbon emission markets (see, for example, [20,36,11]); determinants of CO₂ allowance prices (see, for example, [2–4,12,34,35,31,32] among many others), comovements of carbon allowance prices and the prices of other financial assets (see, for example, [15,16]), while other studies have analyzed the relationship between carbon spot and futures prices (see, for example, [47,36,13,14,17,46,5,40], among others).

In this paper, we re-examine the time series properties of CO₂ emission allowance spot prices covering the daily period from 28/2/2007 to 14/05/2014. However, instead of using previous models or approaches already used in the literature such as mixed GARCH models [38], Markov switching and GARCH [6], fractionally integrated asymmetric power GARCH [18], or Markov switching GARCH models [7], we use other recently developed methodologies based on the concept of long run dependence or long memory processes in the context of non-linearities and structural breaks.

Three contributions are made by this work. First, we provide further evidence of the long memory properties of the carbon emission allowance prices along with an analysis of their stability properties across time. In this context, a recent procedure to determine fractional integration with structural breaks is also implemented. Second, we introduce a new model also based on long memory that uses non-linear deterministic trends in the context of fractional integration to describe the carbon emission allowance prices. Third, our selected sample period (28/2/2007–14/05/2014) covers three trading periods from European Union Allowance -EUA- (e.g., Phase I running from 2005 until 2007;

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Phase II going from 2008 to 2012; and Phase III running from 2013 until 2020). To the best of our knowledge, our research is the first paper that analyzes the persistence property of CO₂ allowance price accounting for structural breaks and non-linearities with CO₂ data from the three Phases of the European Union Emissions Trading System –EU ETS.

The remainder of the paper is structured as follows: Section 2 reviews the literature on CO₂ emissions. Section 3 briefly describes the methodology and justifies its application in the context of CO₂ emissions. Section 4 presents the data and the main empirical results, while Section 5 contains some concluding comments.

2. Literature review on modeling CO₂ emission allowance prices

Some papers that analyze price drivers of CO₂ emission allowance prices are [2–4,12,34,37,35,50,31,32] among many others. Price drivers of CO₂ emission allowances are temperature [3,34], prices of fuel, crude oil, coal and natural gas [3,34,37,33], macroeconomic variables, production structures change and population growth [12,18,50]. Alternatively, other studies in carbon emission markets focus mainly on modeling the relationship between carbon emission spot and futures prices (see, for example, [47,36,13,14,40,28] among others).

On the other hand, only a few papers have examined the time series properties of CO₂ emission allowance prices using daily data [38,43,21,6,18,35,7]. For example, Paoletta and Taschine [38] use a mixed-normal GARCH model with data from CO₂ in Europe and SO₂ in the US, and their finding indicate that these modeling approaches are only valid for a very specific period at the end of Phase I.

Alternatively, Sheifert et al. [43] used a finite horizon, continuous-time, stochastic equilibrium model, obtaining that CO₂ prices present a time and price-dependent volatility structure. Daskalakis et al. [21] use three main markets for emission allowances under the EU ETS (namely Powernext, Nord Pool and ECX) to study the effects of abolishing banking on futures prices during Phase I, and to develop a framework for pricing and hedging of intra-phase and inter-phase futures and options on futures. Their empirical results suggest that emission allowance spot prices are likely to be characterized by jumps and non-stationarity. Benz and Trück [6] also examine the spot price dynamics of CO₂ emission allowances in the EU ETS and their findings support the adequacy of the models which capture characteristics such as skewness, excess kurtosis and in particular different phases of volatility behavior in the returns. Finally, in a recent study by Benschop and López [7], a Markov Switching GARCH model is proposed on daily spot market data from the second trading period of the EU ETS, concluding that the proposed model justifies very well the feature behavior in spot prices (e.g., volatility clustering, breaks in the volatility process and heavy-tailed distributions).

Our paper also uses daily data on CO₂ emission allowance prices and extends the previous literature in two directions. Firstly, by using standard long memory and $I(d)$ techniques, and then, by extending this approach to the case of structural breaks and non-linear deterministic trends.

3. Methodology

As mentioned earlier, we first employ standard $I(d)$ techniques, and we estimate the fractional differencing parameter, d , in the following model,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, \dots \quad (1)$$

where y_t is the observed series, β_0 and β_1 are the coefficients corresponding to an intercept and a linear time trend, and x_t is assumed to be $I(d)$, where d can take any real value. Therefore the error term, u_t , is $I(0)$. Here, we will employ two approaches. The first one is parametric and is based on the Whittle function in the frequency domain [23] assuming that the error term is first a white noise process, and then autocorrelated, with autoregressions, and also throughout the model of Bloomfield [9]. The latter is a non-parametric approach to approximate ARMA processes with a short number of parameters and that accommodates extremely well in the context of fractional integration.¹ In addition, the Lagrange Multiplier (LM) method of Robinson [41] will also be conducted. This method has the advantage that it can be implemented even in nonstationary contexts and thus, it does not require preliminary differencing in the case of nonstationary series. A semiparametric “local” Whittle method [42], widely employed in empirical studies will also be implemented in the empirical section.

The above specification in (1) imposes a linear time trend in the model that might be too restrictive in the context of carbon emissions. Thus, we also implement a new method proposed by Cuestas and Gil-Alana [19] characterized for allowing the inclusion of non-linear trends by means of using Chebyshev polynomials in time. The model considered here is

$$y_t = \sum_{i=0}^m \theta_i P_{iT}(t) + x_t, \quad t = 1, 2, \dots \quad (2)$$

with m indicating the order of the Chebyshev polynomial, and x_t following an $I(d)$ process of the same form as in Eq. (1).

The Chebyshev polynomials $P_{iT}(t)$ in (2) are defined as:

$$P_{0,T}(t) = 1, \\ P_{i,T}(t) = \sqrt{2} \cos(i\pi(t-0.5)/T), \quad t = 1, 2, \dots, T; \quad i = 1, 2, \dots \quad (3)$$

(see [30,44] for a detailed description of these polynomials). Bierens [8] uses them in the context of unit root testing. According to Bierens [8] and Tomasevic and Stanivuk [45], it is possible to approximate highly non-linear trends with rather low degree polynomials. If $m=0$ the model contains an intercept, if $m=1$ it also includes a linear trend, and if $m > 1$ it becomes non-linear-the higher m is the less linear the approximated deterministic component becomes.

An issue that immediately arises here is how to determine the optimal value of m . As argued in Cuestas and Gil-Alana [19], if one combines (2) with the second equation in (1), standard t -statistics will remain valid with the error term being $I(0)$ by definition. The choice of m will then depend on the significance of the Chebyshev coefficients. Note that the model then becomes linear and d can be parametrically estimated or even tested as in Robinson [41], Demetrescu et al. [22] and others (see [19]).

Finally, in view of the existence of non-linearities in the data, we also conduct another approach proposed in Gil-Alana [27] that permits us to consider fractional integration in the context of structural breaks at unknown periods of time. The model examined here is as follows:

$$y_t = \beta_i^T z_t + x_t; \quad (1-L)^{d_i} x_t = u_t, \quad t = 1, \dots, T_b^i, \quad i = 1, \dots, nb, \quad (4)$$

where nb is the number of breaks, y_t is once more the observed time series, the β_i 's are the coefficients corresponding to the deterministic terms; the d_i 's are the orders of integration for each sub-sample, and the T_b^i 's correspond to the times of the unknown breaks. This specific functional form of this method can be found in Gil-Alana [27]. Note that given the difficulties in distinguishing

¹ See Gil-Alana [26].

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