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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.

Contents

1. Introduction

Modeling and explaining CO_2 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 CO_2 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 CO_2 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 CO_2 allowance price accounting for structural breaks and non-linearities with CO_2 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 CO_2 emissions. Section 3 briefly describes the methodology and justifies its application in the context of CO_2 emissions. Section 4 presents the data and the main empirical results, while Section 5 contains some concluding comments.

2. Literature review on modeling CO_2 emission allowance prices

Some papers that analyze price drivers of CO_2 emission allowance prices are [2–4,12,34,37,35,50,31,32] among many others. Price drivers of CO_2 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 CO_2 emission allowance prices using daily data [38,43,21,6,18,35,7]. For example, Paolella and Taschine [38] use a mixed-normal GARCH model with data from CO_2 in Europe and SO_2 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 CO_2 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 CO_2 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 CO_2 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,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1-L)^d x_t = u_t, \qquad t = 1, 2, \ldots \tag{1}$$

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

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

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 $P_{i,T}(t)$ in (2) are defined as:

$$P_{0,T}(t) = 1,$$

$$P_{i,T}(t) = \sqrt{2}\ \cos\left(i\pi(t-0.5)/T\right), \qquad t = 1, 2, \ldots, T; \quad i = 1, 2, \ldots \tag{3}$$

(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:

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

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].

between models with fractional orders of integration and those with broken deterministic trends [24,29], it is important to consider estimation procedures that deal with fractional unit roots in the presence of broken deterministic terms.

4. Empirical results

Our sample covers daily data on CO_2 emission allowance spot prices, covering the period from 28/2/2007 to 14/05/2014, with the start and end date being purely data-driven. The data is sourced from Datastream of Thomson Reuters.

The first thing we do in this section it to make plots of the time series and its log transformation. A downward trend is clearly observable, with possible structural breaks in the series. As we mentioned earlier, our selected sample period runs from 2007 to 2014 and covers three trading periods from EU ETS. Macroeconomic variables are also likely to have an impact on our selected CO_2 emission allowance prices. We observe a positive trend in the first part of the sample period from 2007 and 2008 and a downward trend from 2008 to 2014 corresponding with the economic and financial crisis.

We start by estimating d in Eq. (1) under the three standard cases examined in the literature, i.e., the case of no deterministic terms (i.e., $\beta_0=\beta_1=0$ a priori in Eq. (1)); including an intercept (β_0 unknown and $\beta_1=0$ a priori), and with a linear time trend (β_0 and β_1 unknown), assuming that the error term u_t is white noise, AR (1) and Bloomfield-type. The results in terms of the estimated values of d and the 95% confidence bands of the non-rejection values of d using Robinson's [41] method are reported in Table 1.

The results indicate strong evidence of unit roots (i.e. $d=1$) in the majority of the cases. A similar result is also found in Alberola et al. [4], Daskalakis et al. [21], Chevalier [13,14], Arouri et al. [5] and Hammoudeh et al. [33] who also obtain evidence of a unit root for CO_2 emission allowance prices. Thus, for the original prices, this is the case in all the cases considered; however, for the logged prices, we observe some values which are statistically significantly below 1 though with values very close to 1.

We also estimated the fractional differencing parameter using a semiparametric Whittle method. Here we use a "*local*" Whittle estimate in the frequency domain, based on a band of frequencies that degenerates to zero. This method [42] is implicitly defined by:

$$\hat{d}=\arg\ \min_d\left(\log\ \overline{C(d)}-2\ d\frac{1}{m}\sum_{j=1}^{m}\log\ \lambda_j\right), \tag{5}$$

$$for\ \ d\in(-1/2,1/2);\quad \overline{C(d)}=\frac{1}{m}\sum_{j=1}^{m}I(\lambda_j)\lambda_j^{2d},\quad \lambda_j=\frac{2\pi j}{T},\quad \frac{1}{m}+\frac{m}{T}\to 0,$$

where m is the bandwidth parameter, and $I(\lambda_j)$ is the periodogram of the time series. Under finiteness of the fourth moment and other mild conditions, Robinson [42] proved that:

$$\sqrt{m}(\hat{d}-d_o)\to_d N(0,1/4)\quad as\ \ T\to\infty,$$

where d_o is the true value of d and with the only additional requirement that $m\to\infty$ slower than T.[2]

The results, for different bandwidth numbers, are presented in Table 2, and the estimates of d are also displayed in Fig. 2 for values of m (bandwidth)=1, … 200. The results are very consistent with those reported in Table 1 with the parametric methods. Thus, the unit root is almost never rejected, and we only observe a few number of cases of mean reversion ($d<1$) for the logged prices in Fig. 2.

Table 1
Estimated values of d and their corresponding 95% confidence bands.

	No regressors	An intercept	A linear time trend
a) Original data			
White noise	**1.01 (0.98, 1.03)**	**1.01 (0.98, 1.04)**	**1.01 (0.98, 1.04)**
AR (1)	–	**0.98 (0.94, 1.02)**	**0.98 (0.94, 1.02)**
Bloomfield-type	**0.98 (0.94, 1.02)**	**0.97 (0.93, 1.02)**	**0.97 (0.93, 1.02)**
b) Log-transformed data			
White noise	**0.99 (0.96, 1.03)**	**0.97 (0.93, 1.00)**	**0.97 (0.93, 1.00)**
AR (1)	–	0.92 (0.87, 0.96)	0.92 (0.87, 0.96)
Bloomfield-type	**0.98 (0.94, 1.03)**	0.91 (0.87, 0.95)	0.90 (0.86, 0.97)

In bold, evidence of unit roots at the 5% level.

Table 2
Estimates of d based on a "local" Whittle semiparametric approach.

Bandwidth	m	Original	Log	95% lower $I(1)$	95% upper $I(1)$
$(T)^{0.3}$	9	**0.851**	**0.897**	0.725	1.274
$(T)^{0.4}$	20	**1.033**	**0.978**	0.816	1.183
$(T)^{0.5}-3$	40	**1.084**	**0.974**	0.869	1.130
$(T)^{0.5}-2$	41	**1.066**	**0.966**	0.871	1.128
$(T)^{0.5}-1$	42	**1.076**	**0.973**	0.873	1.127
$(T)^{0.5}$	43	**1.065**	**0.956**	0.874	1.125
$(T)^{0.5}+1$	44	**1.049**	**0.932**	0.876	1.124
$(T)^{0.5}+2$	45	**1.035**	**0.929**	0.877	1,122
$(T)^{0.5}+3$	46	**1.046**	**0.927**	0.878	1,121
$(T)^{0.6}$	92	**1.061**	**0.921**	0.914	1.085
$(T)^{0.7}$	196	**1.042**	**1.007**	0.941	1.058

In bold, evidence of unit roots at the 5% level.

In a recent study, Hammoudeh et al. [33] consider nonlinearities and asymmetries in CO_2 allowance prices, taking into account that CO_2 allowance prices can be relatively high (low) during boom (recession) periods or when new low carbon technologies are slow in entering the market. Following this previous idea, we focus on the possibility of non-linearities in the data. For example, Benz and Trück [6] show that CO_2 emission allowance prices exhibit non-linear dynamics that can be modeled using Markov Switching models. In order to capture non-linearities, we use the procedure developed by Cuestas and Gil-Alana [19] testing fractional integration with non-linear (Chebyshev) polynomials. The considered model is now:

$$y_t=\sum_{i=0}^{m}\theta_i P_{iT}(t)+x_t,\quad (1-L)^d x_t=u_t, \tag{6}$$

where $P_{i,T}(t)$ are the Chebyshev time polynomials as described in Eq. (3) and $m=1$, 2 and 3. As earlier mentioned, if $m=0$ the model contains an intercept, if $m=1$ it adds a linear trend, and if $m>1$ the model becomes non-linear, and the higher m is the less linear the approximated deterministic component becomes.

The results using this approach are presented in Table 3 and they are very similar to those reported in Table 1 for the linear case. Thus, we obtain evidence of unit roots in the original series, and the same for the logged prices though in this case we detect some cases with a small degree of mean reverting behavior ($d<1$). Though not reported, none of the coefficients for the (linear and/or nonlinear) deterministic terms were statistically significant, so we can conclude by saying that there is no evidence of non-linear deterministic components in the series examined.

We finally conduct the approach developed in Gil-Alana [27] for testing $I(d)$ processes with structural breaks. Time trends were found to be statistically insignificant, so in the case of structural

[2] Extensions of this approach can be found in Velasco [48,49], Phillips and Shimotsu [39] and Abadir et al. [1] among many others.

Table 3
Estimates of d and 95% confidence band with Cuestas and Gil-Alana [19] approach.

	$m=1$	$m=2$	$m=3$
i) Original data			
White noise	**1.01 (0.98, 1.04)**	**1.01 (0.98, 1.04)**	**1.01 (0.98, 1.05)**
AR (1)	**1.01 (0.99, 1.03)**	**1.01 (0.99, 1.03)**	**1.00 (0.98, 1.05)**
ii) Log-transformed data			
White noise	**0.96 (0.93, 1.00)**	**0.96 (0.93, 1.00)**	**0.99 (0.93, 1.06)**
AR (1)	0.96 (0.94, 0.99)	0.96 (0.94, 0.99)	**0.97 (0.93, 1.05)**

In bold, evidence of unit roots at the 5% level.

breaks they correspond to mean shifts in the level of the series. Thus, the model examined is:

$$y_t = \beta_0^{(i)} + x_t, \quad (1-L)^{d^{(i)}} x_t = u_t, \quad t = 1, 2, \ldots T^{(i)} \tag{7}$$

and $i=1$, 2 and 3 (2 breaks, in the original prices) and $i=1$, 2, 3 and 4 (3 breaks) in the logged prices. Results are reported in Table 4.[3]

Two breaks are detected in the original prices, and three in the logged transformed series. The detected structural break dates are 11/02/2009 and 12/12/2011 in the original series, and 16/02/2009, 16/12/2011 and 22/01/2013 in the logarithm form. The detected breaks are related with the following events. The first and the second breaks are related with Phase Two of EU ETS where the spot price of an EU allowance experienced a significant decrease (see Fig. 1). The first date break is related with the huge impact of the impact of economic recession and financial crisis on energy use reducing the spot price while the second break is also related with a new decrease in CO_2 emission allowance spot prices. The last break on 22/01/2013 is related with the beginning of Phase Three of EU ETS where the European carbon market was characterized by persistently low prices for emission allowances in 2013. Furthermore, several features are detected here. First, we observe a reduction in the degree of integration when we move from one sample to another. This happens for the two series examined. Also, there is a reduction in the levels of the series at different subsamples as we move from one to another. With respect to the first of these two issues we notice a linear decrease in the degree of persistence as we move across the subsamples. For example, focusing on the log-transformed data with white noise disturbances, we observe that the estimated value of d is 1.06 for the first sub-sample; 1.00 for the second one; it decreases to 0.99 in the third, and 0.86 in the fourth sub-sample, and more importantly, the unit root hypothesis is rejected in the first sub-sample in favor of $d>1$; the unit root null ($d=1$) cannot be rejected in the second and third subsamples, and it is rejected in favor of mean reversion ($d<1$) in the fourth subsample. This pattern is observed also in the unlogged series and for all types of disturbances. Especially noticeable is the fact that the unit root null is rejected in favor of mean reversion (i.e., $d<1$) in the last sub-sample in all cases examined with the logged data, and also in the original data with autocorrelated disturbances. Thus, shocks become transitory in the last periods of the sample. In addition, Fig. 3 shows a reduction in the levels of the CO_2 emissions from one sub-sample to another. This is likely to be related to its pro-cyclical behavior, i.e., CO_2 tends to increase (decrease) when the overall economy is also growing (slowing down) leading to higher (lower) carbon prices [32].

In general, our results have interesting implications in terms of the efficient market hypothesis (EMH) for the carbon emission allowance spot prices. First, of all we show that if we do not allow for the breaks in the data, and consider the entire sample we are likely to believe that the carbon emission allowance spot prices are indeed characterized by a random-walk data generating process, i.e., the EMH holds. However, when we investigate this result by allowing for breaks, we observe that the full-sample result does not necessarily hold in the most recent sub-samples, to the extent that, the carbon emission allowance spot prices are now mean-reverting, or in other words, the EMH no longer holds in the spot market based on more recent data. So from a technical point of view, not allowing for breaks is likely to spuriously detect long-memory and hence incorrectly characterize the univariate properties of a time series – a point we discussed earlier. While, previous studies found that CO_2 allowance prices are $I(1)$ variables (see, for example, [4,21,13,14,5,33]), in this paper our estimated values of d tend to decrease over time suggesting that the effect of shocks to the CO_2 allowance price have become more transitory in nature over time. From a policy perspective, our result suggests that while, policy involvement would have been required to cause the spot prices to revert back to equilibrium, in more recent periods, the market will correct itself, *albeit* at a slow rate. In addition, this also implies that, now there are roles for other variables (such as oil, natural gas, coal, and electricity prices as discussed in [32]) in explaining the behavior of the carbon emission allowance spot prices. To put it differently, we can use information on these variables to predict the path of the carbon emission allowance spot prices.

5. Final conclusions

This paper examines the time series dynamics of the CO_2 emission allowance prices using daily data from 28/2/2007 to 14/05/2014. For this purpose we have employed long range dependence techniques based on fractional integration, including also an analysis of its stability across time. The results can be summarized as follows. First, we show that the original series as well as its log-transformation are both highly persistent, with orders of integration equal to or slightly smaller than 1. This result is obtained using parametric, semiparametric and non-parametric techniques of fractional integration. Non-linear deterministic trends were also examined in this context, and using the methodology developed by Cuestas and Gil-Alana [19] the series were also found to be $I(1)$ but no evidence of non-linearities was found in the data. Finally, the possibility of structural breaks was also investigated and the results indicate the existence of two breaks in the original series and three breaks in the log-transformed data. In both cases, we observe a substantial reduction in the value of d suggesting that, if structural breaks are unaccounted for then we are likely to overestimate the degree of persistence in the CO_2 allowance price, and also that the effect of shocks to the CO_2 allowance price have become more transitory in nature over time.

The results obtained related to the high degree of persistence for the first subsamples suggest that in the event of negative exogenous shock, strong active climate and energy policies should be adopted to recover the original level of CO_2. However, the degree of persistence obtained in the last subsamples (see Table 4) with values below 1 show that the level of CO_2 does not need such active policies in this context to recover its original value when an event hits or shocks its value over time.

Finally, according to the European Commission [25], Member States of the European Union are on track to meet their Kyoto target and emissions will be 21% lower in 2020 than in 1990. However, the European Commission [25] also considers that the European Union still needs to implement additional policies and measures to meet their 2020 national emission reduction target.

[3] The number of breaks is endogenously determined by the model itself.

Table 4
Estimates of *d* based on [27] with structural breaks.

	i) Original data			
	1st subsample	2nd subsample	3rd subsample	
	28/02/2007 11/02/2009	12/02/2009 12/12/2011	13/12/2011 14/05/2014	
White noise	1.04 (0.98, 1.10)	1.00 (0.96, 1.05)	0.94 (0.89, 1.00)	
AR (1)	1.00 (0.93, 1.08)	0.97 (0.91, 1.05)	0.89 (0.80, 0.99)	
Bloomfield-type	0.99 (0.92, 1.08)	0.98 (0.91, 1.05)	0.89 (0.80, 0.99)	
	ii) Log-transformed data			
	1st subsample 28/02/2007 16/02/2009	2nd subsample 17/02/2009 16/12/2011	3rd subsample 19/12/2011 22/01/2013	4th subsample 23/01/2013 14/05/2014
Wh. noise	1.06 (1.01, 1.12)	1.00 (0.95, 1.05)	0.99 (0.91, 1.10)	0.86 (0.79, 0.96)
AR (1)	1.03 (0.97, 1.10)	0.95 (0.89, 1.02)	0.91 (0.67, 1.12)	0.75 (0.61, 0.89)
Bloomfield	1.03 (0.96, 1.11)	0.94 (0.88, 1.02)	0.93 (0.81, 1.10)	0.74 (0.63, 0.89)

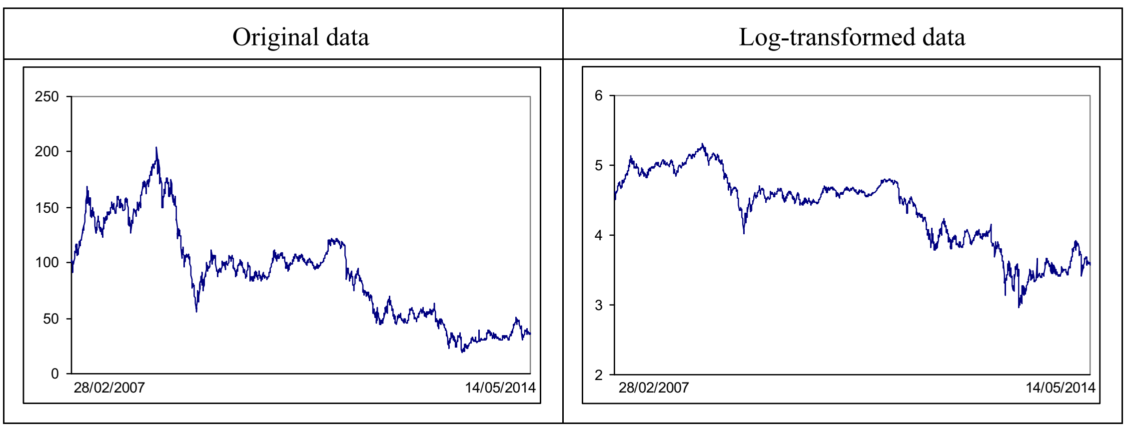

Fig. 1. Time series plots.

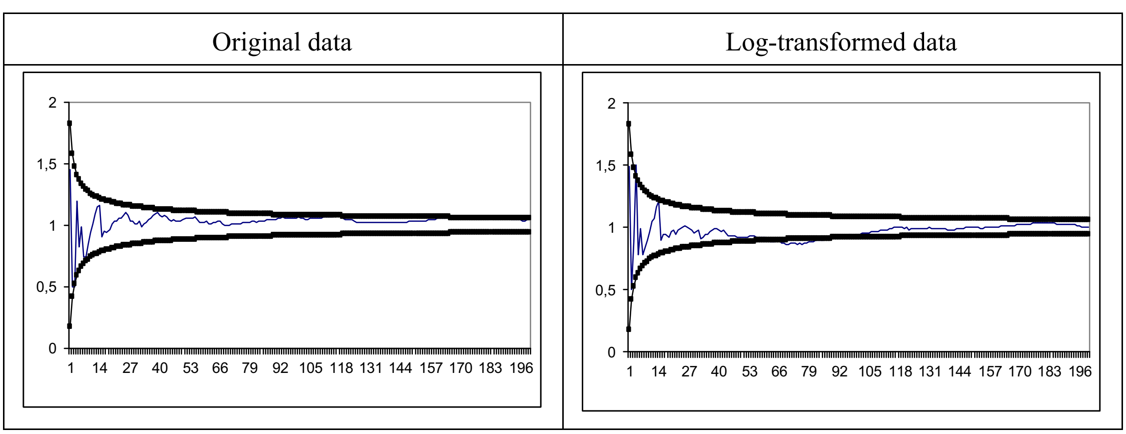

Fig. 2. "Local" Whittle estimates of *d* [42]. The thick liens refer to the 95% confidence bands corresponding to the unit root case.

Two potential factors could explain the recent relatively more transitory impact of CO_2. First, the downward behavior of the CO_2 emission allowances prices is in line with the financial crisis and the global recession that followed, with slowing down of the economy is likely to reduce pollution and the transaction in the spot market. Second, the introduction of active energy and climate policies to meet Kyoto Protocol (and also EU 2020) and low carbon technologies is now enforced in most of the OECD economies and could also play a role also in the reduced degree of persistence. According to Chang et al. [10], local government should establish scientific emissions reduction plan and strict emissions quota allocation rules while European authorities should strengthen international cooperation in the greenhouse emission reduction. Previous policies, tend to reduce the demand for trade in CO_2 emission market which also push down CO_2 emission allowances prices as well as its persistence. Further research is required to corroborate these conclusions.

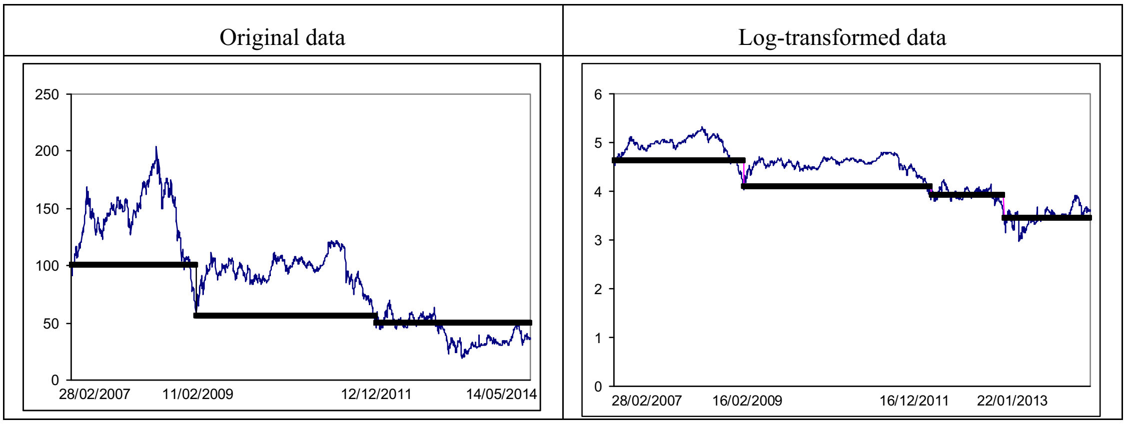

Fig. 3. Time series plots and estimated trends.

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