Volatility in CO2 EUA returns: a FIGARCH approach

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Resumo: *This paper models volatility in CO2 EUAs emission returns using a FIGARCH approach. Our findings overwhelmingly suggest that conditional variance in CO2 emissions allowance returns is stationary and mean reverting autocorrelations decaying at a hyperbolic rate. Hence, a shock to forecast of future conditional variance will be temporary but it will last longer.*

Our results have important policy implications, as the knowledge of the stochastic properties of the conditional variance is of particular relevance for decisions on investment in abatement activities, for the design of arbitrage strategies to take advantage of momentary opportunities in energy markets. Moreover, our results also suggest the importance of accounting for the interactions of volatility in the EUAs CO2 emissions market with energy sectors, the economy, and climate, both in terms of modeling and forecasting.

Palavras chave*: CO2 emission prices, volatility, FIGARCH*

Jel Classification: *C22, E52, E58, F30, G10*

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1. Introduction

The aim of this study is to use an ARMA-FIGARCH model to analyze and measure the presence of long memory in the volatility of returns associated with the price of European Union Allowances (EUAs hereafter) in the European Union Emissions Trading System (EU ETS hereafter).

Established in 2005 by Directive 2003/87/EC, the EU ETS was mainly aimed at the energy production sector and industrial processes (namely the ferrous metal, mineral, refining and paper pulp industries) and brought about an important change from the traditional GHG environmental policy which had basically been supported by command-and-control instruments. It brought a shift of emphasis to a strategy which was based on the decision-making process for the allocation of resources used by companies, and sought to achieve two important objectives under an emissions cap-and-trade regime: a) to provide incentives for industry to reduce GHG emissions to the desired levels; and b) to contribute to advancing the implementation of low-carbon technologies and energy efficiency. Currently, the EU ETS market is held to have prime responsibility for the 22.5% reduction in total GHG emissions by the 28 EU Member States between 1990 and 2014 [see, among others, Zhang & Wei (2010)].

The literature on the volatility of returns associated with the EU ETS market concentrates principally on the factors that impact variation in price, and is still very focused on the pilot phase of this market. Some of these factors arise from the supply side and others from the demand side of emissions allowances [see among others, Neuhoff et al. (2006), Kattner et al. (2007), Woerdman (2008), Clò (2010), Ellerman and Buchner (2008), Alberola et al. (2008), Alberola et al. (2009), Parsons at al. (2009) and Helm (2009).]

There is now a budding field of literature specifically focused on the stochastic properties of CO2 prices and returns, and providing evidence for heteroskedasticity in the conditional variance in daily CO2 returns [see Paolella and Taschinin (2008), Conrad (2012) and Liu and Chen (2013)].

This article contributes to expanding and enriching the debate in the literature on the modeling and explanation of EUA price movements. In particular, our work adds to the very small set of approaches which assume that current prices embrace all the information on the key factors that determine the level and variability of prices in the EU ETS in order to assess and measure the presence of long memory in the process of generating data for the carbon price time series. We do so by testing for fractional integration using an $ARMA(p,q)-FIGARCH(p,d,)$ model. Long memory implies a significant dependence between observations which are widely separated in time, and therefore the effects caused by shocks tend to decay slowly, although still mean-reverting in nature. Fractional integration models were introduced by Granger and Joyeux (1980), Granger (1980), Sowell (1992a, b), Baillie

(1996), and Palma (2007) and provide greater flexibility in assessing the characteristics of time series.

The remainder of this article is organized as follows. Section 2 provides a brief technical description of the methodology used. Section 3 presents the data set and some description of the data. Section 4 discusses the empirical findings, first considering the traditional unit roots approach and then using our fractional integration approach. Finally, Section 5 provides a summary of the results, and discusses their implications for energy and environmental policies.

2. *Volatility in CO2 prices: The IGARCH and the FIGARCH models*

One of the characteristics which the results of empirical applications of the traditional class of Generalized AutoRegressive Conditionally Heteroscedastic (GARCH) models have in common is the presence of persistence in the estimated conditional variance [see Engle (1982), among others]. This finding led Engle and Bollerslev (1986) to introduce what they termed the Integrated GARCH model (or IGARCH). This model is to the covariance-stationary GARCH model class as $I(1)$ processes (1) are to $I(0)$ processes in the case of the conditional mean. IGARCH models impose a constraint such that the sum of the ARCH and GARCH components must be one. In the specific case of an $IGARCH(1,1)$ model, it must be ascertained that $\alpha_1 + \beta_1 = 1$, and the process becomes a unit root in variance.

The $FIGARCH(p, d, q)$ process can be represented in the traditional way by the conditional variance equation [see Baillie et al. (1996)]:

$$[1 - \beta(L)]\sigma_t^2 = \omega + [1 - \beta(L) - \phi(L)(1 - L)^d \, u_t^2] \qquad (1)$$

where L represents the phase shift operator, $\phi(L) = [1 - \alpha(L) - \beta(L)]$, $\alpha(L) = \alpha_1 L + \cdots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \cdots + \beta L^p$ are the phase shift polynomials. In addition, it is assumed that the $ARMA(p, q)$ roots of the polynomials $\phi(L)$ and $[1 - \beta(L)]$ are within the unit circle. In addition, as with the $GARCH(p, q)$, process, which can be represented as an $ARMA(p, q)$ process where $\{u_t^2\}$ is the conditional mean, a $FIGARCH(p, d, q)$ process can also be represented by an $ARFIMA(p, d, q)$ process where $\{u_t^2\}$ is the conditional mean,

$$\phi(L)(1 - L)^d\, u_t^2 = \omega + [1 - \beta(L)]v_t \qquad (2)$$

with $v_t \equiv u_t^2 - \sigma_t^2$. In this class of FIGARCH models, the short-term behavior of the time series is captured by the ARMA components, while the long-run dependence is captured by the fractional integration coefficient d [Sowell (1992a)].

The estimation strategy used to test the presence of long memory in the rate of CO2 allowance returns is based on the methodology put forward by Bollersev and Mikkelsen (1996), and involves the use of two models, $ARMA(2,0) - IGARCH$ and $ARMA(2,0) - FIGARCH(1, d, 1)$. Taking the daily frequency of the data into account, we can cater for the impact that non-transaction days have on the variance in rate of return on the first day after a break in trading. We do this by including the variable "gap_t" for the number of days without allowance transactions between time t and time t-1 [see, for example, French and Roll (1986)].

3. Data: sources and description

Our data set consists of daily CO2 equivalent (CO2e, hereafter) close prices on EU ETS, from January 2, 2008 through May 23, 2014, for a total of T = 1,628 observations. Data was obtained from EEX. Following the usual practice, we transform daily CO2e prices into a daily returns series $y_t = 100.\ln(p_t/p_{t-1}),\ t = 1, \dots, T$. The time subscript t refers to trading days. Daily data are also available for the first EU ETS period (between January 2005 and December 2007), but due to the pilot nature of this phase, they were not considered in this study. Figure 1 plots the daily prices for CO2e emissions and Figure 2 plots daily returns.

Figure 1- Daily prices of CO2e emission Allowances in the ETS

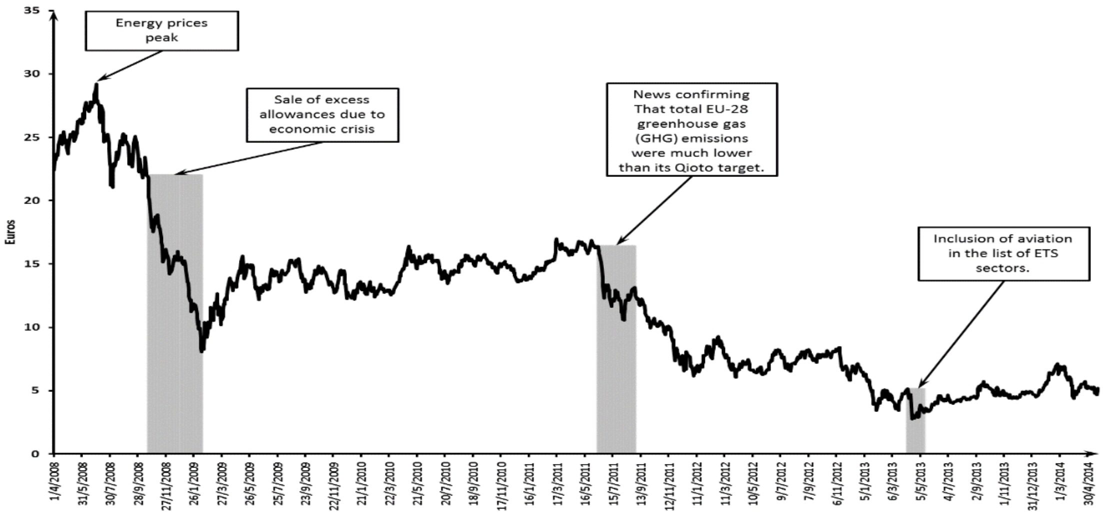


Figure 2- Daily CO2e emission allowances returns in the ETS

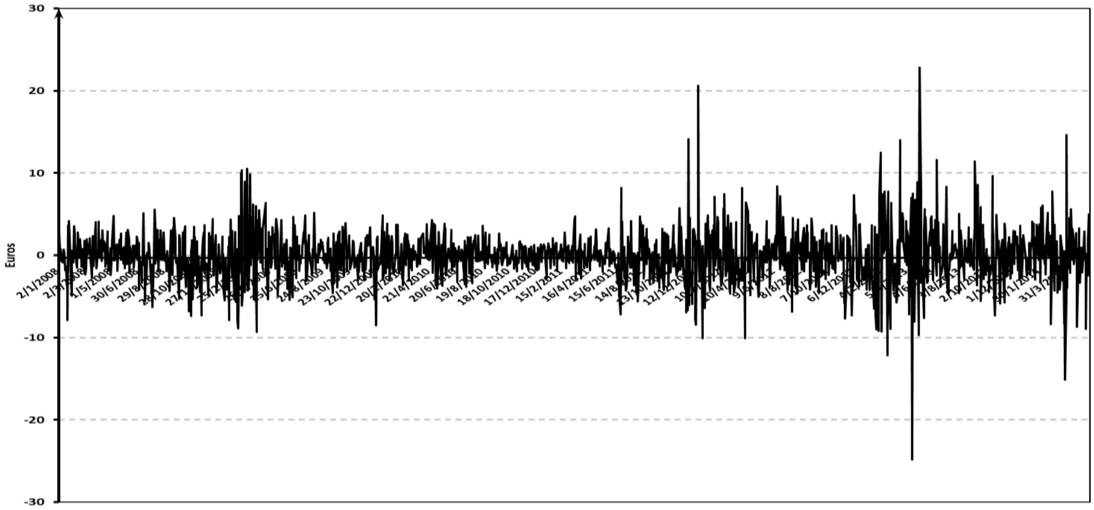


Table 1 presents some summary statistics, where μ stands for the mean, σ stands for the standard deviation and σ/μ stands for the coefficient of variation. The coefficient of variation shows the extent of variability in relation to the mean.

Table 1 - Summary statistics for daily CO2 prices and returns

Sub-periods	m3	m4	μ	σ_μ	$\left\lvert \sigma_\mu / \mu \right\rvert$
Prices (€)					
2008			22.27	0.226	0.010
2009			13.22	0.099	0.007
2010			14.37	0.064	0.004
2011			12.95	0.180	0.014
2012			7.37	0.045	0.006
2013			4.46	0.042	0.009
2014			5.58	0.075	0.013
Overall sample	0.593 (0.000)	-0.238 (0.056)	12.02	0.150	0.012
Returns					
2008			-0.115	0.145	1,259
2009			-0.041	0.195	4,717
2010			0.057	0.105	1,856
2011			-0.224	0.184	0,821
2012			0.013	0.187	14,843
2013			-0.001	0.294	498,393
2014			0.131	0.383	2,921
Overall sample	0.008 (0.902)	8.121 (0.000)	-0.041	0.078	1,913

Note: The statistics $m3$ and $m4$ are the standard measures of skewness and kurtosis. Under the null hypothesis of normality they will have asymptotic distributions of $m3 \approx N(0, 6/T)$ and $m4 \approx N(0, 24/T)$

In general, the average price per ton of CO2e for our sample was €12.08, with a mean standard error of 0.150 and a variability coefficient of 1.25% (see Table 1). It can also be seen in Table 1 that the price per ton of CO2e dropped consistently over the sample period from a high of €29.20 on 1 April 2008 to €2.78 on 14 July 2013 (see Figure 1).

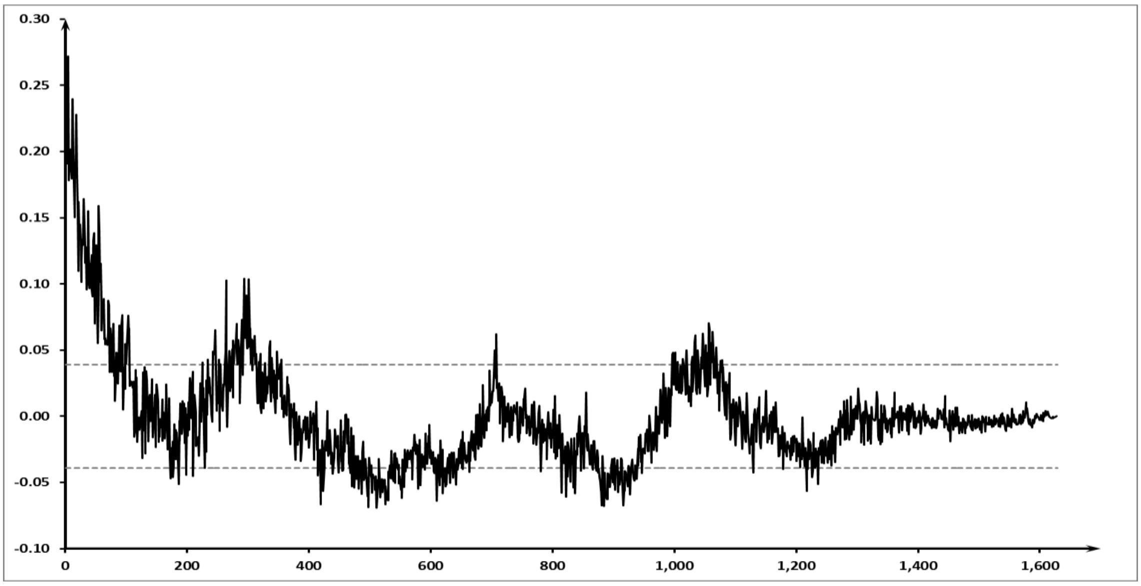
The daily rate of price change reveals a completely different time pattern. Indeed, the average daily value of returns (as a percentage) during the sample period was -0.041%.

Conversely, the average standard error (0.078%) is about twice the average, which suggests great variability in the returns associated with CO2e emissions allowances over the sample period. It is noteworthy that the years 2008, 2011 and 2014 had the highest average daily volatility in price, while the critical years for returns were, 2013, 2012, 2009 and 2014, in this order. Meanwhile, the highest percentage increase in CO2e price was 22.87% on April 17, 2013 and the largest daily percentage decrease was 24.87% three weeks later, on May 5 (see Figure 2). These variations were certainly a result of the combination of several factors that came about in 2013, in April in particular. In fact, 2013 saw the start of accounting of aviation emissions, and the first endpoint for the accounts of these emissions and any compensation for companies in EUAs was in April. This caused great apprehension in the market, which led the European Commission to delay the start of operations of this new legal framework. In addition, that same month, the European Parliament had also scheduled a debate and vote on a proposal from some member states to reduce that year's cap by 900 million tons of CO2e in order to raise the price of CO2e, which made the EUA market highly unstable.

4. Long memory in CO2 returns volatility

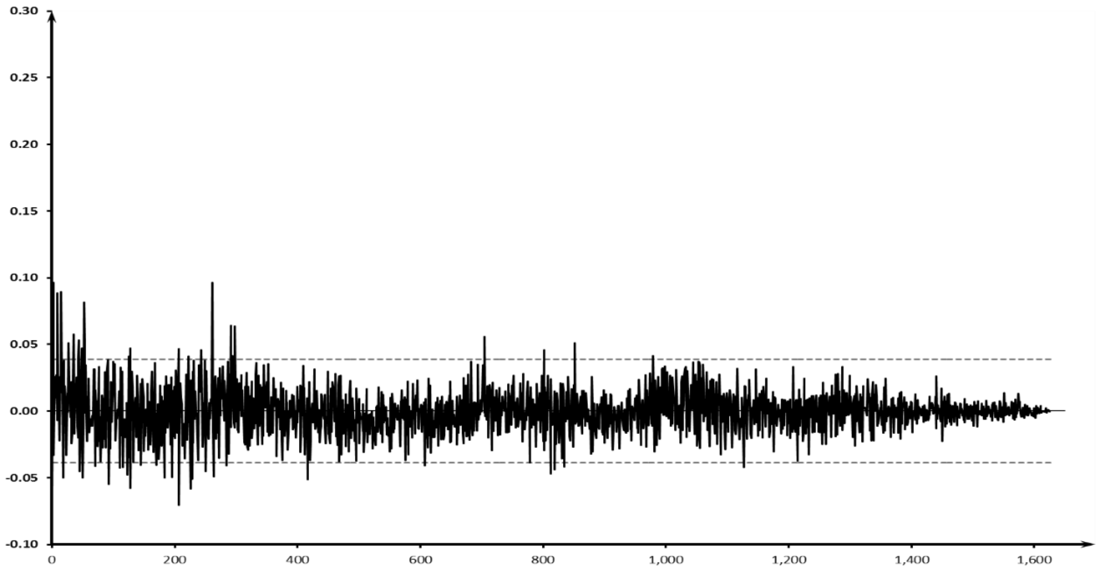
From Figure 3 it is clear a that the absolute return correlations for very long lags frequently exceed the two 95% Bartlett (1946) confidence bands for no serial correlation. The Ljung-Box (1978) test is highly significant for any lag. For example, for lag 516, the Q-tatistic is 3,502.08 compared with the applicable value of the χ^2 distribution for 514 degrees of freedom, which is 567.

Figure 3. Autocorrelations for absolute returns



Note: The 95% confidence bands for no serial dependence are also plotted in the figure

Figure 4. Autocorrelations for the fractionally differences ($d = 0.25$) of absolute returns



In contrast, when we filter the original absolute returns series with a fractional differencing operator $(1-L)^{0.25}|y_t|$, the long-term dependence is substantially reduced, as shown in Figure 4. Indeed, the portmanteau Ljung-Box test for the joint significance for lag 516 is significantly reduced to 567.05, with a p-value of 0.056. Moreover, for all subsequent lags, the decision criterion suggests the absence of serial correlation.

Table 2 shows the results of the IGARCH and FIGARCH models for the entire sample. The Ljung-Box (1978) Q_k portmanteau test for the k^{th}-order serial correlation in $\hat{u}_t$ allows us to confidently reject the null hypothesis of uncorrelated returns. In addition, Table 3 also presents the Ljung-Box (1978) Q_k^2 portmanteau test based on $\hat{u}_t^2$ for homoskedasticity. Under the null hypothesis of conditional homoskedasticity, the statistic Q_k^2 will have a chi-squared distribution with k df. For both models, the null hypothesis is clearly rejected for k = 20, 50 and 100. These two results may be explained by the strong leptokurtosis and left skewness in returns and residuals, which affect the power of the Ljung-Box tests.

Table 2. AR(2)-IGARCH(1,0) and AR(2)-FIGARCH(1,0) models for daily CO2 price returns

$$y_t = \mu_1 y_{t-1} + \mu_2 y_{t-2} + u_t$$
$$h_t = \omega(1-\beta_1)^{-1} + [1-(1-\beta_1 L)^{-1}(1-\phi_1 L)(1-L)^d][u_{t-1}^2 - \delta gap_t] + \delta gap_t$$
$$z_t \equiv u_t\left(\sqrt{h_t}\right)^{-1}, E_{t-1}(z_t) = 0 \text{ and } VAR_{t-1}(z_t) = 1$$

Statistics	**ARMA(2,0)-IGARCH(1,1)**	**ARMA(2,0)-FIGARCH(1,d,1)**
	All sample	**All sample**
AR(1)	0.066 (0.011)	0.060 (0.031)
AR(2)	-0.040 (0.114)	-0.043 (0.099)
$\boldsymbol{\omega}$	5.62 e^{-7} (0.004)	1.49 e^{-6} (0.260)
$\boldsymbol{\beta_1}$	0.905 (0.000)	0.954 (0.000)
$\boldsymbol{\phi_1}$	1.000 (0.000)	0.997 (0.000)
d		0.112 (0.001)
$\boldsymbol{\delta}$	5.79 e^{-6} (0.004)	5.98 e^{-5} (0.001)
Log Likelihood	3617.716	3621.791
BIC	-4.420	-4.420
Q-stat (20)	1044.737 (0.000)	1128.081 (0.000)
Q-stat (50)	1747.888 (0.000)	1889.810 (0.000)
Q-stat (100)	2379.882 (0.000)	2585.229 (0.000)
Q^2-stat (20)	205.018 (0.000)	417.694 (0.000)
Q^2-stat (50)	338.428 (0.000)	760.845 (0.000)
Q^2-stat (100)	463.707 (0.000)	1096.163 (0.000)
m3	-4.4909	-5.0149
m4	35.6806	46.2528

NOTE: p-values in brackets. The values of the Ljung-Box portmanteau test for up to kth-order serial correlation in the standardized residuals $\hat{\varepsilon}_t \hat{\sigma}_t^{-1}$, and the standardized squared residuals, $\hat{\varepsilon}_t^2 \hat{\sigma}_t^{-1}$, are denoted by Q_k and Q_k^2 respectively.
The statistics $m3$ and $m4$ are the standard measures of skewness and kurtosis. Under the null hypothesis of normality they will have asymptotic distributions of $m3 \approx N(0, 6/T)$ and $m4 \approx N(0, 24/T)$.

The estimated value of the dummy variable corresponding to the non-trading period δ is highly significant and has the expected sign in both models. Thus, the volatility of returns tends to increase after non-transaction periods, which is consistent with the empirical evidence for financial markets. However, this result contrasts with the estimated value in the previous GARCH models (and also in the conditional mean). This can be justified by the fact that the dummy only enters these models with a direct effect on the conditional variance equation.

The first column gives the estimated parameters of the general GARCH model with the constraint $\phi_1 = \alpha_1 + \beta_1 = 1$, (or IGARCH). This models the possibility of conditional variance being an $I(1)$ process, that is, an exogenous disturbance in conditional variance will permanently affect the predictions of conditional variance for all future periods. Except for the parameter $ar(2)$ of the conditional mean equation, all estimated parameters are significant at the 1% level. The GARCH parameter is high and, unsurprisingly, very similar to the value obtained for the unrestricted model. However, both the AIC and BIC criteria choose the ARMA(2,0)-IGARCH(1,1) model over the ARMA(2,0)-GARCH(1,1) model.

Table 2 column 2 gives the results of the model estimation in which the possibility of volatility of returns is assumed to be the fractionally integrated process of order "d". The estimate of the fractional parameter d is between 0 and 1, thus allowing both the pure stationary (d = 0) and the unit root case (d = 1) to be rejected. More specifically, the estimated fractional parameter d is statistically significant at the 1% level, it lies within the interval (0.0 e 0.5) and is statistically different from these two bounds at a 1% level. The confidence interval for the estimated fractional integration parameter is relatively narrow and in the positive range. Also, the upper bound is lower than 0.5, thus indicating that volatility in returns is stationary and mean-reverting but exhibits long memory. In addition, the estimated parameters $\hat{\beta}_1 = 0.954$, $\hat{\phi}_1 = 0.997$ and $\hat{d} = 0.112$ satisfy the condition necessary for a non-negative conditional variance of the FIGARCH(1,d,1), models, namely $\beta_1 - d \leq \phi_1 \leq (2-d)/3$ and $d[\phi_1 - (1-d)/2] \leq \beta_1(\phi_1 - \beta_1 + d)$ Once again, the AIC and BIC criteria indicate that the ARMA(2,0)-FIGARCH(1,d,1) model is chosen over all others.

5. Conclusion

This paper models volatility in CO2e EUAs prices using an ARFIMA(2,0)-GARCH(p,q) class of models, using daily CO2e emissions allowances data from January 2, 2008 through May 23, 2014, for a total of T = 1,628 observations. Our results can be summarized as follows.

Our findings on long memory in the volatility of daily EUAs returns complement recent evidence by Conrad (2012) of an asymmetric power fractional differencing process in the conditional variance of intraday carbon returns, as well as by Liu and Chen (2013) on the fractional differencing process in the conditional variance of daily future carbon returns. In addition, the high degree of significance of the estimated fractional integration parameter in the conditional variance of CO2 emission allowances returns differs from the results of Feng et al. (2011), who did not find clear evidence of the presence of long memory. This discrepancy is certainly justified by the fact that our study benefits from a longer time series, which does not include the EU ETS pilot phase (2005-2007) but does include the first year of the third post-Kyoto negotiation period (2013-2020). Furthermore, it should be mentioned that after 2008, the institutional framework changed substantially, with the Commission playing a more influential role in national emission allowance plans, the creation of a single CAP for the EU, its extension to other ETS sectors, in particular aviation, and the introduction of new CO2 gases. In addition, in the third post-Kyoto negotiation period, traditional grandfathering-based allowanced allocation was replaced by an auction-based allocation process along with the creation of both a primary and a secondary CO2 emissions market, and a single EU-wide electronic trade platform [the European Energy Exchange platform – EEX]. At the same time, a system of exceptions was also adopted for the auction scheme for sectors considered to be exposed to the risk of carbon leakage.

Our results have important implications for the decision-making process of the ETS industries. The presence of long memory suggests that returns already incorporate information about the relevant fundamentals to the formation of EUA prices. Thus knowledge about the stochastic properties of the conditional variance is of particular relevance for decisions to invest in abatement activities, for the design of arbitrage strategies to take advantage of momentary advantages in energy markets (oil, carbon and natural gas markets), for decisions on banking and borrowing, and for risk management in general. In addition, knowledge of the long-term presence of volatility in the EU ETS also allows the EU as well as Member State regulatory agencies to better design the regulatory framework for the functioning of this market.

The stochastic properties of the conditional variance of CO2 emission allowance returns are still relevant and should be taken into account when projections in CO2 emissions allowances are used to set prospective scenarios of public policies (either consumption or production based) or even private policies. This is particularly clear in the strategic orientation of some EU member-states in promoting green tax reforms that use the EUAs price as an index of the various instruments of these reforms [Pereira and Pereira (2013)].

Finally, our results also have important implications from a more technical perspective. Indeed, they suggest the importance of accounting for the interactions of volatility in the EUAs CO2 emissions market with energy sectors, the economy, and climate, both in terms of modeling and forecasting, as there is evidence that transitory shocks in conditional variance returns exhibit long memory. Indeed, given the strong connection of the energy and transport sectors to the rest of the economy, the effect of shocks may be transmitted to other sectors and even have impacts on the real economy, such as employment and output.

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