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The erratic behaviour of the EU ETS on the path towards consolidation and price stability

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Abstract

The Kyoto Protocol envisages the use of various instruments to achieve emission reduction targets, one of which is the European Union Emission Trading Scheme (EU ETS), the most important market worldwide for CO_2 emission allowances. The volume of European Union Allowances traded represents over 45% of all the carbon dioxide generated by human activity within the continent. In its first two phases (2005–2012), the behaviour of the EU ETS was erratic, as a result of discretionary policies, an oversupply of allowances and reduced economic activity due to the global crisis. These factors caused excessively low prices that distorted the initial goals of achieving low-carbon solutions. From 2013, changes were made to the market regulation mechanisms in order to correct these structural deficiencies. Empirical analysis of daily prices in the two central phases of the market, following the pattern of ARCH and GARCH models, shows that the measures taken within the EU generated greater confidence and stability in the market and thus reduced volatility. Subsequent price behaviour, following a bullish path, has confirmed the success of the measures taken and their contribution to fulfilling emission reduction targets.

Keywords Kyoto Protocol · Emissions Trading System · EUA trading · Price shocks · GARCH models

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Emissions Trading System EUA trading (EU-ETS) Flexibility Mechanisms Clean Development Mechanism (Kvoto Protocol) CER trading (CDM) Project-based mechanisms Mechanisms for Joint Implementation ERU trading (MJI)

Fig. 1 Flexibility mechanisms included in the Kyoto Protocol

1 Introduction

Constantly rising levels of consumption and the resultant increase in global industrial activity have generated new patterns of production and energy consumption, which are the main cause of the increasing volume of emissions of greenhouse gases (GHG). The presence of these gases in the atmosphere is generating a global climate change which, in turn, has a severe impact on natural resources and socioeconomic systems. Especially relevant in this respect is the role played by carbon dioxide (CO₂), which accounts for over 70% of total GHG emissions, according to the Intergovernmental Panel on Climate Change (IPCC). Three world powers are responsible for the bulk of CO₂ emissions: China, which produces over 29% of the total, followed by North America (21%) and the European Union (11%) (International Energy Agency 2016).

The Kyoto Protocol, adopted in December 1997, is the legal instrument that first set targets for reducing and capping GHG emissions¹ by the largest developed countries and by countries with economies in transition. The 2016 Paris agreement reasserted this commitment, setting the goal of limiting the increase in global average temperature to 2 °C above pre-industrial levels. Despite the difficulties involved in reaching agreements and achieving compliance, certain key energy indicators show that some progress is being achieved. For instance, estimated CO₂ emissions in 2015 presented negative growth, producing a "decoupling of the previously close relationship between global economic growth, energy demand and energy-related CO₂ emissions" (International Energy Agency 2016).

In designing a sustainable environmental policy for the EU, two types of market instrument were considered: on the one hand, those focused on modifying the prices of goods and services, mainly by means of taxes (Villar-Rubio and Huete-Morales 2017). Such instruments are primarily designed to raise revenues, to provide financial or fiscal incentives (through price reductions) and to change the behaviour of producers and/or consumers. Secondly, market instruments may also act on quantities, determining the maximum amount of a substance that may be produced, by means of systems of tradable permits (Quesada-Rubio et al. 2011; Quesada et al. 2010).

Among the latter instruments are flexibility mechanisms (Fig. 1), which can be used as a complement to internal measures and policies to reduce emissions. The most widely

¹ The Kyoto Protocol was drafted with the initial objective of reducing global greenhouse gas emissions, during the period 2008–2012, by 5.2% in relation to 1990 levels.

used flexibility mechanism is the Emissions Trading System (ETS), under which a ceiling (cap) is imposed on the total amount of emissions allowed for a given period of time. Each participant receives a certain amount of emission permits or allowances,² depending on criteria such as historical emission values, or through an auction process. These permits can then be traded in a secondary market. Thus, during the specified period of time, participants who emit less than their quota can sell their surplus permits to others whose emissions exceed their maximum allowable quantity, and thus the price of the permits is determined by the market, through supply and demand.

Many such mechanisms have been implemented or are being evaluated, especially in the last 2 years. The carbon market has a turnover of about 52 billion dollars, including fiscal and market mechanisms (World Bank and Ecofys 2016), a volume of trade that is growing with the involvement of additional countries, and despite the negative impact of certain factors such as the falling price of permits, less stringent caps in some ETS and increased productive efficiency in some sectors, such as the automobile industry, which has invested heavily in clean energies.

The European Union Emission Trading Scheme (EU ETS), created in 2005, is the most important in the world.³ With 31 countries (the 28 members of the European Union plus Iceland, Liechtenstein and Norway), the EU ETS largely determines demand and prices in other markets. Emission permits issued under this trading system are called EUAs (European Union Allowances), and also known as "carbon credits". EUAs account for 70% of the world's CO₂ emissions, and the EU ETS represents approximately 45% of all the CO₂ generated by human activity on the continent, more than two billion tonnes of CO₂, and regulates the emissions of over 11,000 power plants and large industrial facilities (Mazza and Petitjean 2015).

In addition to the above, there are "Project-based mechanisms", consisting of two emission reduction instruments: on the one hand, the Clean Development Mechanism (CDM), which allows countries that have ratified the Kyoto Protocol to obtain Certified Emissions Reductions (CERs) equivalent to one tonne of CO_2 not emitted into the atmosphere, and which, like EUAs, can be sold in a secondary market. CERs are obtained through action on projects that reduce GHG emissions and contribute to sustainable development in developing countries. On the other hand are Mechanisms for Joint Implementation (MJI), which allow countries to obtain Emission Reduction Units (ERUs), by which Member States can anticipate the acquisition of emission credits by carrying out emission reduction projects in other industrialised countries with specified targets (mainly Eastern European or OECD countries).

2 Chronological evolution of the emission permits market

Directive 2003/87/EC regulating the GHG emission allowances trading system within the European Union was implemented on 1 January 2005, covering CO_2 emissions from thermal power stations, cogeneration, other combustion plants with thermal power exceeding

 $^{^{2}}$ Each permit allows the holder to emit one metric ton of carbon dioxide (CO₂), or equivalent amounts of nitrous oxide (NO₂) and perfluorocarbons (PFCs).

³ Similar to the ETS in the European Union, other "Cap & Trade" systems have been adopted in other countries or regions, such as the CCX (Chicago Climate Exchange) created in the USA in 2003, and the NZ ETS (New Zealand Emissions Trading Scheme), applied since 2009 in New Zealand, among many others.



Fig. 2 Chronology of the different phases of the EU Emissions Trading System

20 MW, refineries, coke plants, steel, cement, ceramics, glass and paper mills. Each Member State prepared and submitted to the European Commission its National Allocation Plan (NAP), which would determine the total amount of allowances to be allocated and the allocation procedure. European legislation had prepared the development of the emission permits market in four distinct phases (Fig. 2).

In Phase I (2005–2007), considered as a test phase, at least 95% of the allowances were allocated free of charge. At the end of each year, the Administration verified the actual emissions of each company, so that if a company/facility had emitted more tons of CO_2 than those covered by the allowances received, it had to acquire in the market allowances for the difference and deliver them to the Administration. On the contrary, if the company polluted less, it could sell the leftover permits. If they did not comply with the limit laid down in the NAP, companies could be penalised by a fine of \notin 40 per tonne in excess of the cap allocated in the period 2005–2007, which would increase to \notin 100 in Phase II.

Overestimation of CO_2 emission levels (initially based on forecasts rather than actual measurements) resulted in an over-allocation of allowances, which was transferred to the market as an oversupply. This, coupled with the inability to buy emission allowances and to accumulate them for later use, led to a sharp drop in EUA prices in April 2006 (over 54% in a few days), resulting in a price close to $\in 0$. This adversely affected the perception of the utility of the permits market, and discouraged companies from investing and innovating in clean technologies.

In Phase II (2008–2012), although the volume of free allocations was decreased to 90% and unlimited accumulation of permits was allowed, these measures failed to prevent the oversupply of emission rights. As can be seen in Fig. 3, at the beginning of this period prices rose to almost ε 23 per EUA, reflecting market demand for cumulative emission



Fig. 3 Daily observed prices of CO_2 emission allowances in Phase II (2008–2012) and Phase III (2013–6 May 2016) (in euros)

rights, in the expectation that they would be useful in the future. Nevertheless, over the period as a whole, prices tended to fall, and ended close to \notin 8, due to the excess supply of carbon assets and to the lower demand for EUAs because of the 2008 financial crisis (de Perthuis and Trotignon 2014).

In Phase III (2013–2020),⁴ and in accordance with Directive 2009/29/EC, the NAPs disappeared, and a community approach was adopted, in which the EU set a ceiling for annual global emissions, in view of its emission reduction target. The EU allocates the rights as follows: 43% to be granted by each country free of charge to stipulated companies, and the remaining 57% to be auctioned.

Following this criterion, each industrial facility is assigned a volume of free issues, called "free allocation", taking into account the technological state of each sector and its potential for reducing GHG emissions.⁵ To fill the gap between this free allocation and the real allocation, auctions are held, on a schedule regulated by the EU. Auction prices are set by the law of supply and demand.

However, the problem of excess permits in the market remained, and because these rights were cumulative, normal market behaviour was inhibited. Among the measures considered, such as extending the use of EUAs to other sectors, or establishing a minimum auction price (Brink et al. 2016; Clò et al. 2013; European Commission 2012; Koch et al. 2014; Marcu 2013; Verdonk et al. 2013), the EU proposed two regulatory mechanisms. In the short term, the issuance of 900 million permits would be postponed (back-loading of auctions), so that the market would naturally drain the surplus of EUAs. Furthermore, to facilitate long-term market stability, a Market Stability Reserve (MSR) would be created, as a mechanism to absorb and maintain the rights in excess of 833 million (thus fewer rights would be auctioned); they would then be injected into the market (in multiples of 100 million) if the number of rights fell below 400 million. There are currently 1693 million rights in circulation (European Commission 2017a), and so if the MSR were in operation, it would absorb 860 million rights.

Regulatory uncertainty caused notable price fluctuations (Koch et al. 2014), causing prices to fall sharply to $\notin 2.7$ in April 2013. Since then, the market has taken a favourable view of the measures taken by the European Commission, and so the price of the rights has risen steadily, and for the first time since 2012 it is now above $\notin 8.30$.

In this third period, it is worth noting the rapid growth of the CO_2 price in the summer of 2015, reaching for the first time (since 2012) levels above 8.30. Holiday periods should be more quieter a priori, with few movements in the trading tables and little industrial activity and fall in prices should be expected. However, auctions are reduced practically to half the volume offered in months like August (less liquidity) and energy demand increases due to higher temperatures, so it could explain this price increase that has been repeating more than once during this season on subsequent years.

In short, the emission allowances market is far from being effective in achieving its objectives, and from being efficient in incorporating information into market prices. Many factors have characterised this market, underlying its erratic behaviour since its inception in 2005. The relative immaturity of the market (Seifert et al. 2008), coupled with its semi-public origin (public issuance of rights through private sector platforms),

⁴ Croatia's entry into the EU ETS took place at the start of Phase III.

⁵ Only sectors considered to be at risk of carbon leakage (i.e. production or investment relocation to areas that do not have emission limits, leading to an increase in global emissions) receive a free allowance allocation.

and the continuing uncertainties generated by the lack of a univocal policy in the regulation of the market, all contribute to market inefficiency. However, recent developments have provided grounds for optimism, and the measures adopted between Phases I and II have enhanced market efficiency (Bredin et al. 2014; Medina et al. 2014).

The main aim of this paper is to demonstrate that the measures adopted by the European Commission at the end of Phase II have indeed contributed to improving the functioning of the EU ETS market, and have had a significant impact in Phase III, a period characterised by decreased volatility in the price of CO_2 rights, and have helped smooth the effects of external shocks motivated by political uncertainty. In order to make an empirical comparison, daily oscillations in EUA prices were modelled using GARCH(p,q) models. If our hypothesis is confirmed, this would be consistent with previous research and establish that the new measures were well accepted by the market, as an incentive to participate in the rights market (Venmans 2015). To the best of our knowledge, only one previous study has analysed and compared Phases II and III (Sanin et al. 2015), and none have considered the changes in volatility between the different phases of the project in order to determine the improvement or otherwise of market efficiency.

The CO₂ allowances markets have attracted considerable attention, both among researchers and in professional communities, and numerous studies have examined the behaviour of these markets, in most cases employing autoregressive modelling to explain the volatility of carbon bond yields, and thus determine the greater or lesser efficiency of the market in the first two phases of the ETS (Byun and Cho 2013; Castagneto-Gissey 2014; Feng et al. 2012; Gürler et al. 2016; Rannou and Barneto 2016). Other models have also been used for this purpose, such as autoregressive vectors and Granger causality test (Cummins 2013; Tang et al. 2013), the Roll model that Medina et al. (2014) used to compare the efficiency of Phases I and II, and the joint-expectations microstructural model of security prices proposed by Ibrahim and Kalaitzoglou (2016).

Other ETS are emerging, and so studies limited to certain geographic areas have also been conducted; thus, strategic analyses have been made of the carbon rights markets in China (Liu et al. 2015, 2017) and in India (Kapoor and Ghosh 2014; Pradhan et al. 2017). In order to build efficient strategies of participation in the markets, numerous papers have focused on determining the main drivers of EUA prices (Aatola et al. 2013; Alberola et al. 2008; Chevallier 2011; Creti et al. 2012; Guðbrandsdóttir and Haraldsson 2011; Hammoudeh et al. 2014; Koch et al. 2014; Mansanet-Bataller et al. 2011) and of the recently created EUA options (Chevallier 2013; Daskalakis et al. 2009; Viteva et al. 2014). Others have sought to determine the relations between EUAs and other asset classes, such as CERs (Guðbrandsdóttir and Haraldsson 2011; Nazifi 2013), oil (Yu et al. 2015; Zheng et al. 2013), energy markets in general (Zhang and Wei 2010) or other asset classes (Zheng et al. 2015). A novel and promising standpoint is considering nonlinearities as a better approach, although results are not yet conclusive (Atsalakis 2016; Chevallier 2011; Gil-Alana et al. 2016; Li and Lu 2015). Despite this being a relatively young market, positive results have been achieved by some investment strategies, such as those based on mean reversion (Chang et al. 2013) or on momentum (Crossland et al. 2013). A more extensive review of the literature in this field can be found in Hintermann et al. (2016).

The remainder of this paper is organised as follows. Section 3 presents the data considered, and Sect. 4 describes the empirical method used in the ARCH and GARCH models. Section 5 discusses the empirical findings for Phases I and II, and finally, Sect. 6 presents the principal conclusions drawn and suggests fruitful areas for future research.

3 Data and sample

The behaviour of EUA futures has been erratic from its very beginning and because of different factors. First, it has infringed the principles of non-arbitrage that usually govern financial markets, and this in itself may have constituted a factor of price imbalance (Bredin and Parsons 2016). Second, it has developed an idiosyncratic type of seasonality, due to peaks in trading activity in search for allowances to cover the previous-year legal requirements (Balietti 2016), extreme and unexpected changes in temperatures (Alberola et al. 2008) or its regular calendar structure (Medina et al. 2014).

Nevertheless, most studies of the allowances markets have focused on the futures markets, mainly on the settlement of the year-ahead EUA December futures contract traded on the Intercontinental-European Climate Exchange (ICE-ECX). December expiries are the most active contracts, since the vast majority of EUA transactions consider this maturity to be the most important (Koch et al. 2016). Accordingly, our analysis is based on these data, using daily quotes (in euros) extracted from the Thomson Reuters Eikon database. ICE-ECX, which is part of the ICE conglomerate, is a London-based trading platform that serves as the UK auction house and which trades 96% of futures contracts (Mansanet-Bataller et al. 2011) and more than 80% of spot operations.

The two central market operating periods have been taken as reference: Phase II (2008–2012) and Phase III (2013–2021), in the latter case taking a limit date of 6 May 2016, in order to obtain out-of-sample data with which to test our hypotheses. Phase I (2005–2007) is excluded as it comprised an initial period of "test and learning", of only 3 years' duration (Labandeira and Rodríguez 2006), and was characterised by the existence of jumps and non-stationarity (Daskalakis et al. 2009), impeding reliable comparison between periods.

In addition to the ICE-ECX, there are other auction and trading platforms, such as the Leipzig-based European Energy Exchange (EEX) and two smaller ones, NASDAQ OMX and NYMEX. However, given their low volume of trading, these platforms were excluded from our study. Mizrach (2012) performed a historical review of the integration of European allowances markets.

In 2013, over 40% of the allowances were auctioned and it is estimated that for the period 2013–2020 this level will rise to 50%, since the volume of free allocation rights has decreased by more than the limit. (In 2013, the emission limit of fixed installations closed at 2084 million emission rights.) In EU ETS Phase III (2013–2020), this limit is reduced each year by an initially considered linear reduction factor of 1.74% of the average total amount of rights issued each year in the period 2008–2012.⁶

4 Method

Autoregressive conditional heteroskedastic (ARCH) and generalised autoregressive conditional heteroskedastic (GARCH) models have been widely used to analyse and forecast economic or financial time series characterised by periods of high or low volatility and significant

⁶ In July 2015, the European Commission proposed an amendment to the EU ETS, increasing the speed of decline of the annual emissions cap from -1.74% per year to -2.20%, and enhancing the carbon leakage framework to preserve the competitiveness of European industry (FTI-CL Energy 2017).

kurtosis. The models have been used for diverse purposes, reflecting inflation adjustments (Engle 1983), electricity prices (Garcia et al. 2005), stock prices (Bollerslev et al. 1992; Casas Monsegny and Cepeda Cuervo 2008), options (Hao and Zhang 2013) and crude oil prices (Hou and Suardi 2012).

ARCH and GARCH models have been used satisfactorily in several studies of the prices of the carbon rights, both in their general aspect and in models with variations (Benz and Truck 2009; Chevallier et al. 2011; Conrad et al. 2012; Mazza and Petitjean 2015; Paolella and Taschini 2008).

The GARCH model was proposed by Bollerslev (1986) as a natural generalisation of the ARCH process introduced by Engle in 1983, which recognised the difference between the unconditional and the conditional variance, allowing the latter to change over time as a function of past errors.

The GARCH model provides a longer memory and a more flexible lag structure (Brockwell and Davis 1996), enabling the inclusion of lagged conditional variances. Therefore, these models are usually applied to economic or financial series, since they can show changes in second-order conditional moments, which tend to be correlated in time (periods of high volatility are followed by periods of low volatility and vice versa). On many occasions, too, this type of financial series presents a significant level of kurtosis.

Let the series y_t , in the ARCH(q) model, be $y_t = \varepsilon_t \cdot \sigma_t$ where σ_t is the volatility and ε_t i.i.d. with zero mean and finite variance (white noise). The conditional variance of the series at each time $V(y_t|y_{t-1}) = \sigma_t^2$ is characterised by the following autoregressive process:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \cdot y_{t-i}^2$$

 $\alpha_i \ge 0_{i=1...q}, \alpha_0 > 0$ where α_0 is the minimal value observed of conditional variance (Bera and Higgins 1993). The GARCH(p,q) model adds a term that allows us to assume that the conditional variance also depends on its past observations:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \cdot y_{t-i}^2 + \sum_{i=1}^p \beta_i \cdot \sigma_{t-i}^2$$

where:

$$\alpha_i \ge 0_{i=1...q}, \beta_i \ge 0_{i=1...p}, \alpha_0 > 0, p \ge 0, q > 0, \sum_{i=1}^q \alpha_i + \sum_{i=1}^p \beta_i < 1$$

to ensure stationarity and a conditional variance that is strictly positive.

The descriptive analysis is performed with R software and the *tseries* package. The model is estimated by maximum likelihood estimation with the *fGarch* and *GEVStableGarch* packages.



Fig. 4 Daily log returns of CO₂ emission allowances prices during Phase II (2008–2012) and Phase III (2013–6 May 2016)

5 Results

5.1 Descriptive analysis of CO₂ emission allowances

In view of the volatility presented, we suggest the following approach for modelling CO_2 emission allowance log returns:

$$y_t = \log\left(\frac{P_{t+1}}{P_t}\right)$$

Figure 4 shows the evolution of the log returns during each period, with a low structure in the mean and similar to white noise. However, its distribution is non-normal, and there is great variability in the series, with peaks indicating the presence of heteroskedasticity. For this reason, we must use ARCH models, which assume that the conditional variance depends on the past, with an autoregressive structure, or its generalisation within GARCH models (which associate moving average terms with this dependency).

As can be seen, volatility was substantially lower in Phase III (2013–2016) than in Phase II, especially as of April 2013. In the second phase, there was much uncertainty among investors, as the issuance and allocation of EUAs was highly discretionary, dependent on political decisions and based on estimated data, which often differed greatly from actual data. However, in the current, third, phase, despite continuing direct allocations, most rights are acquired through auctioning, which means that companies can better predict the funds, in US dollars, they will need. The normalisation of market operations and the temporary disappearance of political instability led to a period of greater price stability, manifested in reduced volatility, which was only broken by the discussion and subsequent decision on back-loading and the creation of the MSR.

Analysis of the normality of the data shows that although the skewness is not very high in either period (0.015 and -1.753, respectively), there is a significant level of kurtosis (3.699 and 23.997). The Kolmogorov–Smirnov test of normality confirms this situation, showing that the two sets of log returns do not correspond to a normal distribution (p < 0.001). Figure 5 corroborates this statement.



Fig. 5 Histogram and norm curve of daily EUA log returns from 2 January 2008 to 31 December 2012 and from 2 January 2013 to 6 May 2016

 Table 1
 Estimated parameters, p value, log likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) for the estimated models.

 First period (from 2 January 2008 to 31 December 2012)

Parameter	Estimate	Standard error	p value
ARCH(1)			
Mean	2.038×10^{-4}	5.320×10^{-4}	0.702
\pmb{lpha}_0	4.705×10^{-4}	6.285×10^{-5}	< 0.0001
$\boldsymbol{\alpha}_1$	0.639	0.139	< 0.0001
Degrees of freedom	3.320	0.375 < 0.000	
Log Likelihood: 2959.5	551 normalised: 2	2.339	
AIC: -4.674 BIC: -4.	662		
Conditional distribution	n: Student-t		
GARCH(1,1)			
Mean	3.901×10^{-4}	4.437×10^{-4}	0.379
\pmb{lpha}_0	2.774×10^{-6}	2.075×10^{-6}	0.181
$\boldsymbol{\alpha}_1$	0.118	0.025	< 0.0001
$\boldsymbol{\beta}_1$	0.896	0.019	< 0.0001
Degrees of freedom	4.485	0.612	< 0.0001
Log likelihood: 3051.6	78 normalised: 2.	412	
AIC: -4.817 BIC: -4.	796		
Conditional distribution	n: Student-t		

5.2 Model fitted for Phase II

The non-normality of log returns is common in the prices of assets listed on financial markets (in many cases, broad tails and excessive kurtosis are observed), and the same behaviour is apparent in the market for emission rights. To reflect this behaviour, an ARCH(q) and a GARCH(p, q) model were calibrated to the data, following previous studies of volatility in carbon markets (Zheng et al. 2015).

Table 1 shows the results obtained for the first period, using the maximum log likelihood approach. Several models were analysed for different conditional distributions, the normal distribution and the standardised Student-t distribution of quasi-maximum



Fig.6 Daily EUA log returns from 2 January 2008 to 31 December 2012 for the ARCH(1) and GARCH(1,1) models. Fitted log returns and 95% confidence intervals are shown in the left panel, and volatility in the right

likelihood estimation (QMLE). For the ARCH(1) model, Student-t was taken as the conditional distribution because it provides lower values for the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Moreover, the Student-t specification can provide the excess kurtosis in the conditional distribution, which is not the case with a normal distribution.

Figure 6 shows the fitted values for the ARCH(1) model, together with the volatility of the adjusted series. To ensure the validity and suitability of the model and the effectiveness of our predictions, the estimated residuals should behave as white noise. The Ljung–Box test allows us to check the randomness of residuals (Ljung and Box 1978). In this case, the test reveals significant correlations for a certain number of delays (*p* value < 0.001). The Lagrange multiplier ARCH test (Engle 1982) was also performed, with the null hypothesis of the absence of ARCH components, $\alpha_i = 0_{i=1...q}$ and the alternative hypothesis of conditional heteroskedasticity in the variance process, i.e. the presence of autocorrelation in the squared residuals. Application of this

Table 2 Estimated parameters, p value, log likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) for the estimated models. Second period (from 2 January 2013 to 6 May 2016) 2016)	Parameter	Estimate	Standard error	p value	
	ARCH(1)				
	Mean	7.005×10^{-4}	6.869×10^{-4}	0.307	
	\pmb{lpha}_0	1.088×10^{-3}	3.717×10^{-4}	0.003	
	$\boldsymbol{\alpha}_1$	1.000	0.375	0.008	
	Degrees of freedom	2.470	0.217	< 0.0001	
	Log likelihood: 1852.77 normalised: 2.169				
	AIC: -4.329 BIC: -4.307				
	Conditional distribution: t-Student				
	GARCH(1,1)				
	Mean	7.005×10^{-4}	6.104×10^{-4}	0.251	
	$oldsymbol{lpha}_0$	9.156×10^{-6}	4.554×10^{-6}	0.0444	
	$\boldsymbol{\alpha}_1$	0.118	0.029	< 0.0001	
	$\boldsymbol{\beta}_1$	0.863	0.023	< 0.0001	
	Degrees of freedom	4.016	0.564	< 0.0001	
	Log likelihood: 1930.841 normalised: 2.261				
	AIC: -4.510 BIC: -4.482				
	Conditional distribution: t-Student				

test to the observations showed that heteroskedastic effects were highly significant (p value < 0.001).

To reflect this behaviour, a GARCH(1, 1) model was calibrated to fit the data (Fig. 6). In this model, Student-t was taken as a conditional distribution, since this approach, too, provides lower AIC and BIC values. The ARCH test p value was 0.218, showing the goodness of this fitted model, due to the absence of conditional heteroskedasticity in the variance process. The Ljung–Box test assured the randomness and independence of the standardised residuals. Overall, these measures confirmed the suitability of the GARCH(1,1) model.

5.3 Model fitted for Phase III

In the second period, too, the standardised Student-t distribution was taken into account, since both the AIC and the BIC showed this to be the best distribution for the log returns adjustment (Table 2). The Lagrange multiplier ARCH test did not indicate the presence of heteroskedastic effects (p value = 0.995) and so it did not seem necessary to use a GARCH model for the correct adjustment of log returns in this period. However, the Ljung–Box test indicated that the standardised residuals were not random and independent, but were correlated (p value < 0.001). For this reason, a GARCH model was fitted to the series, and in this case, there was no correlation between the standardised residuals. Likewise, with the GARCH model (1,1), the ARCH test indicated no heteroskedastic effects (p value = 0.965). Accordingly, this model is considered optimum for the log returns adjustment. Figure 7 shows the results of these two models.

In conclusion, the GARCH(1,1) model is suitable for the fitting of this type of financial series, in which we work with log returns. In terms of series volatility (standard deviation), it is interesting to know how this changes over time. Figure 8 shows that in the first period,



Fig. 7 Daily EUA log returns from 2 January 2013 to 6 May 2016 for ARCH(1) and GARCH(1,1) model. Fitted log returns and 95% confidence intervals (left panel), volatility (right panel)



Fig. 8 Volatility with 50 ahead predicted values (in red) for the first period, 2 January 2008–31 December 2012 (left panel), and for the second period, 2 January 2013 to 6 May 2016 (right panel)

the volatility is expected to increase considerably, while in the second, the variability of the series is predicted to be much lower.

6 Conclusions

The EU ETS arose as a means of fulfilling the commitments made in the Kyoto Protocol, to move towards a low carbon future and to achieve the goal of limiting the global average temperature increase to 2 °C above pre-industrial levels. Allowances were claimed to be a key driver of this transformation, in the belief that high CO_2 prices would push major GHG producers to consider technological change and to invest in greener, more efficient sources of energy. However, the permits market turned out to be inefficient, largely due to its immaturity.

The direct allocation mechanism, a typical feature of an intervened market, did not constitute a real incentive to pollute less, since companies could access the market to acquire the necessary rights to cover their excess pollution. In addition, the fines of \notin 40 and \notin 100 per tonne were insufficient to be coercive. Many other factors also contributed to the relative failure of the market in its early years. Thus, the oversupply of rights in the initial stages, coupled with falling demand due to reduced economic activity during the crisis, uncertainty over the discretionary allocation of rights, and contradictory effects on other policies (in particular, on renewable energies), altogether aggravated the continuing decline in the prices of quoted rights. These factors highlighted the imperfections of the rightstrading system and the ineffectiveness of carbon policies in promoting the search for lowcarbon solutions (Gulbrandsen and Stenqvist 2013) and in overcoming companies' distrust in the market (Venmans 2015).

Nevertheless, much progress has been made in the design of the allowances market since Phase III. In this paper, we show that EUA price volatility decreased during the two periods considered, which is indicative of improved market functioning, and of a clear trend towards stability. The increase in the rate of emissions through auctioning, the normalisation of market operations, the adoption of new measures, both short term (back-loading) and long term (MSR), together with the temporary disappearance of political instability, have helped raise confidence in the ETS, thus producing greater price stability (Fan et al. 2017; Perino and Willner 2016).

Despite the problems identified along this paper, the outlook is good with regard to the contribution made by the EU ETS to reducing carbon emissions in the EU (European Commission 2017b), not only because of the improving market efficiency and the increasing confidence placed in this mechanism, but also due to the current positive slope of the forward curve of EUA futures (Bredin and Parsons 2016).

The results of this work can enrich both practitioners and researchers. Authorities should be aware that the main problem facing the EU ETS is that of low prices, which make it impossible to generate incentives in the short or long term to invest in green energy and thus reduce carbon levels (FTI-CL Energy 2017). Findings show that the changes made between Phase II and Phase III were relevant in improving market efficiency, but that they are probably not enough. New regulatory measures are needed, such as the introduction of a tax to guarantee a minimum price for rights (Brink et al. 2016) or the modification of cap levels (Koch et al. 2014), in order to achieve EUA prices that will effectively reduce carbon levels by 2050. It is also worth noting that several other countries are developing similar carbon markets, like India or China. The latter, for instance, learnt from the

European experience, and has recently created a carbon market with a "soft cap" (flexible) in which carbon credits (allowances) are allocated according to the actual emissions figures, and restricted to the power sector (Gan 2018). The conclusions of this work could guide authorities to explore and predict the impact of new legal measures and the extension to other industries. For academics, the results of this study reassert the optimality of GARCH models to describe the behaviour associated with fluctuations in the carbon rights markets, which in turn could be used in extended research on the main drivers of carbon prices.

This work is not exempt from limitations. First, the track record of the EU ETS market is relatively short, and it is still subject to several idiosyncrasies, which limits the possibility to extrapolate the results. Another limitation is that Phase III is still in progress by the time this work is written, so the efficacy of legal measures would be better checked at the end of the period.

Many significant aspects remain to be studied in future research, including the seasonality of the market, the control over arbitrage, discretionary allocations for more efficient performance and best practices in comparison with other markets, such as those established for sulphur dioxide and nitrogen oxide. Researcher could also focus on the use of novel statistical approaches that can be applied (especially nonlinear approaches), recently developed, that could complement the results from more classical techniques.

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