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Understanding volatility dynamics in the EU-ETS market

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We study the short-term price behavior of Phase 2 EU emission allowances. We model returns and volatility dynamics, and we demonstrate that a standard ARMAX-GARCH framework is inadequate for this modeling and that the gaussianity assumption is rejected due to a number of outliers. To improve the fitness of the model, we combine the underlying price process with an additive stochastic jump process. We improve the model's performance by introducing a time-varying jump probability that is explained by two variables: the daily relative change in the volume of transactions and the European Commission's announcements regarding the supply of permits. We show that (i) sharp increases in volume have led to increased volatility during the April 2005–December 2007period but not for the period beginning in January 2008, and (ii) announcements induce jumps in the process that tend to increase volatility across both periods. Thus, authorities face a trade off between disseminating information effectively and promoting market stability.

Keywords: EUA market, EU ETS, carbon emission trading, Garch model, normal mixture
JEL Classification: C16, C32, C51, C53, Q52, Q53

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1. INTRODUCTION

In 2005, the European Union established a region-wide cap on emissions and created a market for pollution allowances, called the EU Emissions Trading Scheme (EU ETS). The objective of this scheme is to efficiently reduce European emissions at the EU level. In this market, installations can exchange their surpluses or deficit of allowances (called EUAs). The EU ETS has been implemented in phases: the preliminary phase (Phase 1) ran from 2005 to 2007, Phase 2 began in 2008 and finished in December 2012 and Phase 3 begun in January 2013 and will end in December 2020. Because Phase 2 was the period of the actual implementation of the Kyoto Protocol objectives, banking of allowances was not allowed between Phase 1 and Phase 2 but was allowed between Phase 2 and Phase 3. This point is particularly important; although Phase 1 and Phase 2 prices have followed completely different patterns since April 2006, Phase 2 and Phase 3 prices depend on identical fundamentals: the supply and demand factors that have an impact on the right to emit one ton of CO_2 in the EU after December 2007 (Mansanet-Bataller and Sanin, 2014).[4] For this reason, we focus on Phase 2 and Phase 3 prices in this paper. It is notable that it has been possible since 2005 to trade futures contracts that underlie Phase 2 allowances (the right to emit one ton of CO_2 in the EU beginning in 2008). Thus, the period from April 2005 to December 2007 featured interphase trading, whereas intraphase trading was featured from January 2008 until May 31, 2013 (the end of the sample period). In this paper, we analyze the short-term price behavior of Phase 2 prices by dividing the timeline into two subsamples to distinguish between interphase and intraphase trading. To this end, we study Phase 2 prices during the EU ETS trial phase, on one hand, and we study Phase 3 prices beginning, in fact, during the actual beginning of Phase 2 in January 2008, on the other hand.

Installation-level trading began in January 2005; by the beginning of 2006, the volume of transactions had already increased by a factor of 10 (Ellerman and Joskow, 2008). The development of the EU ETS market has also been affected by the increasing market participation of intermediaries, *i.e.*, risk managers, brokers and traders, who may be trading on behalf of their clients or holding their own stock of EUAs. The market has gained both in complexity and in flexibility as intermediaries have introduced an increasing range of new instruments, such as futures, forward contracts and other derivatives. In this regard, many observers believe that the creation of the EU ETS has been a success, whereas others remain skeptical. In particular, the rules behind the price formation mechanism and the price dynamics are still unclear. While some authors support the argument that the EUA price responds to market fundamentals – such as energy prices, extreme weather conditions and economic growth (see Bunn and Fezzi, 2009, Mansanet-Bataller et al., 2007, Alberola et al., 2008, Hintermann, 2010 and Creti et al. 2012) – that affect the production of CO_2 and thus demand and supply of the EUAs, others find no such evidence and favor a pure time-series approach (see Milunovich and Joyeux, 2010, Paolella and Taschini, 2008, Benz and Trück, 2008, Chesney and Taschini, 2012, Seifert et al., 2008 and Chevallier et al., 2011). An adequate assessment of short-term price and volatility dynamics in the EU ETS

[4] In April 2006, the EC published the real emissions of the permitted installations under the EU ETS for 2005, which were much lower than the allowances distributed. The banking restriction provoked the decline on Phase 1 prices that finished at levels near zero while Phase 2 prices remained near pre-announcement levels.

is crucial because accurately measuring and forecasting market risk is a key factor for portfolio management and hedging to realize efficient trading strategies and to make informed investment decisions.

In order to shed light on this issue, we analyze the short term price and volatility dynamics of Phase 2 and Phase 3 allowances from April 22, 2005 to May 31, 2013 as a sole price series. We model the conditional mean and variance of returns within an ARMAX-GARCH framework. The standard approach based on the Gaussianity assumption is rejected due to the presence of a number of level and volatility outliers. Furthermore, the presence of additive outliers in the process, if not directly accounted for, typically induces bias in the parameters governing the level and variance dynamics and may result in the detection of spurious non-strationarity. Consequently, we rely on a Bernoulli mixture of Gaussian distributions (BMN) to allow for endogenously determined additive jumps in the price process. Individual distributions in the mixture can be interpreted as different regimes while the mixing law gives the probability of each regime (Alexander, 2004 and Alexander and Lazar, 2006). We find that a two-regime model based on a BMN proves adequate to fit the data.

Paolella and Taschini (2006) have adopted a similar modelling strategy for Phase 1 prices. They propose a three-component mixture which identifies two different GARCH-type volatility dynamics plus a constant variance component. Although their model does not account for an additive jump component, they provide solid arguments to support the use of a mixture of distributions, including the extreme flexibility of the model, the fact that it induces time-varying skewness and kurtosis (see also Hansen, 1994, Harvey and Siddique, 1999, Rockinger and Jondeau, 2002 and Brännäs and Nordman, 2003) and the accuracy of the out-of-sample VaR forecasts.[5]

An alternative approach, based on a two-regime Markov Switching model, has been proposed by Benz and Trück (2009). They argue that the occurrence of spikes in EUA prices and volatility during Phase 1 might be caused by changes in policy and the regulatory framework, such as announcements regarding the National Allocation Plans (NAPs, the document elaborated by the Member States and approved by the EC in which the country cap was fixed for Phase 1 and Phase 2) or fluctuations in production levels resulting from unexpected changes in market fundamentals (such as fuel prices and weather conditions). However, their hypothesis cannot be directly tested because they assume that the probability that governs the switch between the regimes is constant, which yields few economic insights.

The procedure based on the use of a GARCH-type model with mixed innovations to fit an underlying price process combined with an additive jump component has been proposed in other contexts by Vlaar and Palm (1993), Vlaar (1994) and Beine and Laurent (2003). Their approach is appealing because it provides useful insights regarding the occurrence of jumps and their economic interpretation. In this paper, the determinants and the occurrence of jumps are further investigated by allowing the probability associated with the jump component to vary over time and to depend on exogenous variables. In particular, we explicitly account for two drivers of the shifts between regimes: the daily relative change in the volume of transactions and the change in the regulatory environment that is induced by the European Commission's disclosure of information.

[5]For an extensive overview of the properties of the mixture of distributions, see Alexander and Lazar (2006) and Haas et al. (2004), among others.

Our results suggest that large incoming volumes have a destabilizing effect, which translates into large negative returns and sudden volatility movements only in the preliminary phase, *i.e.*, prior to January 2008. This result is consistent with Gabaix et al. (2006) and Milunovich and Joyeux, 2010. The latter states that during the trial phase, trading in the EU ETS was concentrated among a few leading players and characterized by a low number of transactions. Our results show that from January 2008 on this characterization is no longer accurate: the market has developed and, as a consequence, large incoming volumes no longer have a destabilizing effect. Most notably, the GARCH estimates of EUA prices from January 2008 on show a degree of market maturity that is worthy of a financial series belonging to the SP500.

The impact of EC announcements on EUA prices is comparable to the effect of Central Bank interventions on the exchange rate market assessed by Beine and Laurent (2003) in the sense that they induce jumps and tend to increase volatility. The instability following the EC announcements regarding the cap for Phase 2 that were released before the beginning of Phase 2, *i.e.*, until December 2007, can be explained by the unexpected relative scarcity of EUAs for the second phase: the adopted NAPs were revealed to be substantially more restrictive than the target proposed by each member state. In fact, the emission cap approved by the European Commission for Phase 2 (*i.e.*, the sum of the national allocations) was less then 90% of the total emission target proposed by the member states[6]. The instability following the announcements released beginning in January 2008 can be explained by the efforts undertaken by the regulator to further decrease the number of permits available and the new rules for releasing the supply of permits.

The reminder of the paper is organized as follows. Section 2 briefly discusses the main features of the EU ETS market and describes the data used in the empirical analysis. Section 3 presents the standard ARMAX-GARCH model and a set of test statistics used for its validation. Section 4 presents the Bernoulli mixture of normals and its extension that allows for a time-varying jump probability. Section 5 concludes.

2. STYLIZED FACTS AND DATA DESCRIPTION

The EU ETS covers up to 46% of European CO_2 emissions coming from more than 11,000 high-volume energy-using installations in power generation and manufacturing across the 28 European Union countries, the EEA-EFTA states (Iceland, Liechtenstein, Norway) and the flights to and from the EU and the three EEA-EFTA states.[7] During Phase 1 and Phase 2, installations received periodically a free amount of pollution allowances that could be traded on any of the applicable exchanges (e.g.. Powernext, European Climate Exchange and Nordpool) or over the counter (OTC). Unused allowances with vintage belonging to the period 2005-2007, *i.e.*, corresponding to Phase 1, expired at the end of the phase and could not be banked and used during Phase 2. After the announcement of real emissions for the year 2005, the market appeared to be about 4% long, provoking the EUA Phase 1 prices to fall from 29.5 euros to less than 12 euros over just a few days. In 2006

[6]The yearly cap during Phase 1 was 2.298 billion tons of CO_2, whereas in Phase 2, the cap was set to 2.081 billion tons.

[7]EU ETS factsheet: http://ec.europa.eu/clima/publications/docs/factsheet_ets_en.pdf, last visited 19/05/14.

and 2007, this tendency was confirmed. As a consequence, the EUA Phase 1 prices converged rapidly to zero and market agents focused rapidly on Phase 2 prices.

Therefore, in this paper, we analyze the short-term price and volatility dynamics of Phase 2 and Phase 3 as a sole price series. More specifically, we consider the returns on daily December 2008 futures prices traded at the Intercontinental Exchange (ICE) since the beginning of trading (April 22, 2005) to the expiry of the contract and we roll it over with the nearest December futures contract up through the end of the sample period on May 31, 2013. The reason for this choice is that we are always considering the more liquid contract representing Phase 2 and Phase 3 allowance prices. We compute returns (r_{EUA}) as the first difference of the natural logarithm of the price series. Figure 1 shows the evolution of Phase 2 and Phase 3 EUA prices, in addition to the returns on prices.

FIGURE 1 ABOUT HERE

Following the previous literature (Mansanet-Bataller et al., 2007, Alberola et al., 2008, Mansanet-Bataller and Keppler, 2010, and Creti et al., 2012), we consider, as possible market fundamentals, several month-ahead fuel prices and weather indexes. The choice regarding the energy variables is explained by the fact that the main EU ETS sector is the power sector, as emphasized by Mansanet-Bataller et al., 2007, and demand for these allowances depends on energy consumption (that is generally explained by weather variables and industrial activity), on the one hand, and on fuel prices, on the other. We thus use the more representative prices for energy in Europe to model the returns and volatility dynamics of carbon prices. In other words, (i) the daily Month-Ahead Future Natural Gas price (in pounds per therm) traded on the ICE; (ii) the daily coal Month-Ahead Future price CIF ARA (in dollars per ton); (iii) the daily Future Calendar Peak price for electricity (in euros per MWh) traded on Powernext; and (iv) the daily Month-Ahead Brent Crude Future price negotiated on the Intercontinental Futures Exchange (in dollars per barrel). All energy variables considered in this study were converted into euros using the European Central Bank exchange rate.[8] Returns are denoted r_{gas}, r_{coal}, r_{elec}, r_{oil} respectively. Additionally, Alberola et al. (2008) justify the use of month-ahead prices by arguing that installations do not need to hold allowances matching their emissions levels daily and that energy needs are generally met by forward contracting. Thus, changes in month-ahead prices best reflect changes in EUA prices due to changes in industrial expectations. Further, we consider a weather index based on a weighted average of deviations from historical temperatures, following Alberola *et al.* (2008). The economic rationale behind using this index is that extremely high and extremely low temperatures both increase energy demand (for air conditioning or heating, respectively) and therefore carbon prices. Based on this index, we create two dummies: D_{tmp_lo} and D_{tmp_hi} that account for temperatures in the lowest and highest fifth percentiles, respectively. As discussed in the introduction, we consider two subsamples, that is, we distinguish trading that takes place before and after January 2008. The main reason for such a choice is that we wish to distinguish intraphase trading from interphase trading because the change in the institutional framework may impact the results. Additionally, from January 2008 on, even if agents expected the need for new generation capacity, power prices dropped drastically due to the decrease in demand that was driven by the European

[8] http://www.ecb.europa.eu/stats/exchange/eurofxref/html/index.en.html, last visited 19/05/14.

recession and the financial crisis. The recession also had an impact on other sectors covered by the EU ETS, particularly in the cement sector. As a result, the price in the EU ETS also decreased drastically. The changes discussed herein might induce changes in market fundamentals, which is another good reason for considering two subsamples. Summary statistics are reported in Tables 1, 2 and 3.

TABLE 1 ABOUT HERE

TABLE 2 ABOUT HERE

TABLE 3 ABOUT HERE

The previous tables show that EUA returns (r_{EUA}) exhibit negative skewness and a large excess kurtosis both in the full sample and in each of the subsamples considered. All the other variables are characterized by excess kurtosis and positive skewness. The only exception is the return on oil, for which both skewness and kurtosis coefficients are very close to those implied by the Gaussian distribution.

The presence of excess kurtosis in r_{EUA} means that extreme values for the returns (either positive or negative) occur with a frequency that is higher than that implied by the Gaussian distribution. Indeed, the occurrence of outliers is primarily responsible for the rejection of the Gaussianity assumption for EUA futures returns.

We explicitly consider the relative change in the daily volume of future contracts traded on the ICE (r_{vol}) and a binary variable (D_{NAP}) that accounts for the European Commission's announcement (details are reported in Table 4) as a determinant for the occurrence of jumps. The presence of outliers can also be motivated by other specific events, such as changes in abatement decisions. Although it may be difficult to identify specific dates for such changes, these are accounted for in our analysis because their impact is included in the constant of the jump probability.

TABLE 4 ABOUT HERE

TABLE 5 ABOUT HERE

3. BENCHMARK APPROACH

The starting point for the investigation of the EUA price determinants of returns and volatility dynamics is the ARMAX-GARCH framework. This model, widely used in the literature, allows for the presence of exogenous regressors and specifically accounts for conditional heteroskedasticity and serial dependence in the returns. To assess the relevance of the ARMAX-GARCH setting and to discriminate between competing specifications, we suggest the set of four diagnostic tests detailed in the remainder of this Section.

3.1. ARMAX-GARCH model

Consider the stochastic process $r_t = p_t - p_{t-1}$, where p_t is the natural logarithm of the EUA price. The conditional mean of the process is expressed as

$$\Phi(L)r_t = \beta X_{t-1} + \Psi(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{2}$$

where $\Phi(L) = 1 - \sum_{i=1}^{m} \varphi_i L^i$ and $\Psi(L) = 1 + \sum_{i=1}^{n} \psi_i L^i$ are the usual AR and MA polynomials of order, m and n, respectively. Ω_t is the information set at time t, and L is the lag operator such that $L^k x_t = x_{t-k}$ $(k > 0)$ and X_{t-1} is a matrix of lagged regressors (up to a constant). The normality assumption is justified by the fact that the Gaussian Quasi-Maximum Likelihood (QML) estimation delivers consistent estimates even when the normality assumption is rejected, provided that mean and variance are correctly specified (see Weiss, 1986 and Bollerslev and Wooldridge, 1992 among others).

For the conditional variance, we consider the $GARCH(p, q)$ specification (Bollerslev, 1986), that is

$$B(L)\sigma_t^2 = c + A(L)\varepsilon_t^2 \tag{3}$$

with characteristic polynomials $B(L) = 1 - \sum_{i=1}^{q} b_i L^i$ and $A(L) = 1 + \sum_{i=1}^{p} a_i L^i$.

The model is estimated by QML. The sample log likelihood is given by

$$LLF = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{T}\frac{\varepsilon_t^2}{\sigma_t^2} \tag{4}$$

where T is the sample size, which is maximized numerically for $(\beta, \varphi_k, \psi_l, c, a_i, b_j)$, $k = 1, ...m; l = 1, ..., n; i = 1, ..., p; j = 1, ..., q$.

3.2. Diagnostic tests

To correctly estimate the risk borne by an agent trading on the EUA market, the choice of an adequate distribution is crucial. Therefore, to discriminate between model specifications and to verify distributional assumptions, we devote particular attention to diagnostic tests.

Following Vlaar (1994) and Beine and Laurent (2003), we focus on the following set of statistics. First, we consider two tests for the estimated skewness (b_3) and kurtosis (b_4) coefficients of standardized residuals. Second, we check the hypothesis of independent and identically distributed (*iid*) residuals by using the statistic proposed by Brock *et al.* (1996) (BDS test). The statistic is asymptotically standard normal and depends on two bandwidth parameters: a number of embedding dimensions (m) and the dimensional distance (ϵ), see Brock *et al.* for technical details. We set m equal to 6, as suggested by Kanzler (1999), and ϵ such that the first correlation integral is equal to 0.7. Following Kanzler (1999), we performed the test by also setting the first correlation integral equal to 0.8 and different values of m. The results are robust across all combinations. Testing the *iid* hypothesis is crucial to interpret the results of the last test, the Pearson goodness-of-fit test. Indeed, the rejection of the *iid* hypothesis would make the interpretation of the results unclear. The Pearson goodness-of-fit test compares the empirical distribution of standardized residuals to the theoretical distribution. It requires choosing a number of cells g and, for *iid* observation and under the null of a correct distribution, the statistic is distributed as a chi-square with $g - 1$ degrees of freedom. The number of cells, which is to be chosen proportionally to the sample size, is set to 30; see Palm and Vlaar (1997) for further details. The results of the tests for each specification appear together with the estimation results. Preliminary results (Model 1 in Table 6) that are based on the standard setting introduced so far suggest the rejection of the Gaussian distribution at standard significance levels, according to the Pearson goodness-of-fit test. In fact, the standardized residuals show excess skewness (b_3) and kurtosis (b_4) with respect to the normal distribution.

The presence of excess kurtosis in the returns means that extreme values (either positive or negative) occur with a higher frequency than is implied by the Gaussian distribution. This evidence is confirmed when using the procedure developed by Doornik and Ooms (2005) for detecting outliers. Indeed, we find a number of additive level and variance outliers occurring over the period considered.[9]. Finally, the coefficient estimates for the variance dynamics suggest a (possibly) spurious violation of the covariance stationarity assumption.

4. BERNOULLI MIXTURE OF NORMALS

The high number of extreme returns relative to the sample size requires the introduction of an alternative approach that allows the modeling of level and variance shifts. Further, the series of EUA future returns are not symmetric and therefore a Gaussian distribution alone is unable to fit the data. We combine a Gaussian distribution and an additive stochastic jump process. The resulting mixture of distributions has the advantage of accounting for excess skewness and kurtosis (Vlaar, 1994, Alexander and Lazar, 2006). Several parametrizations have been suggested for the mixing law (see, for instance, Vlaar, 1994). We focus on the Bernoulli mixture of Gaussians. Its basic assumption implies that the mixing law for the return densities is Bernoulli. The advantage of this parametrization is its intuitive interpretation: the individual distributions in the mixture represent different regimes, whereas the mixing law gives the probabilities of each regime (Alexander, 2004 and Alexander and Lazar, 2006).

Given the stochastic process $r_t = p_t - p_{t-1}$, with conditional mean $\mu_t = E(r_t \mid \Omega_{t-1})$ and time varying conditional variance $\sigma_t^2 = E(r_t^2 \mid \Omega_{t-1})$, the mixture process can be defined as

$$\begin{array}{lll} r_t = \mu_t + \sigma_t z_t & & \text{with probability } 1-\lambda \\ r_t = \underbrace{\mu_t + \sigma_t z_t}_{\textit{continuous comp.}} & + \underbrace{\tau + \delta z_t^*}_{\textit{additive jump comp.}} & \text{with probability } \lambda \end{array} \tag{5}$$

where z_t and z_t^* are *iid* $N(0,1)$ and λ is the probability of having a level and variance shift and represents the parameter of the mixing law. Finally, τ and δ^2 are the mean and variance of the jump distribution, respectively, and $1/\lambda$ represents the average interval between two consecutive jumps.

The model can be rewritten as:

$$\begin{aligned} r_t &= \mu_t + \lambda\tau + \varepsilon_t; \qquad (6) \\ \varepsilon_t &\mid \Omega_{t-1} \sim (1-\lambda)N(-\lambda\tau, \sigma_t^2) + \lambda N(\tau - \lambda\tau, \sigma_t^2 + \delta^2). \end{aligned}$$

To ensure condition $0 < \lambda < 1 \ \forall t$, we use the following logistic transformation

$$\lambda = 1 - (1 + \exp(\gamma_0))^{-1}. \tag{7}$$

Because a linear combination of normally distributed random variables is also normal, the combination in (6) results in a discrete mixture of normals.

Given the ARMAX-GARCH setting detailed in Section 3, we express the mean

[9] These results are not reported here for purposes of brevity but are available upon request.

and variance in equation (6) as

$$\begin{aligned}\mu_t &= \beta X_{t-1} + \sum_{i=1}^{m} \varphi_i r_{t-i} + \sum_{i=1}^{n} \psi_i \varepsilon_{t-i}; \qquad (8)\\ \sigma_t^2 &= c + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2.\end{aligned}$$

We consider lagged values of the exogenous variables (X_{t-1}) such that the pair (r_t, σ_t^2) are measurable with respect to the information available at time $t-1$,, which ensures that the model is completely forecastable.

The log likelihood of this distribution is given by

$$\begin{aligned}LLF &= -\frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T} \log\left[\frac{1-\lambda}{\sqrt{\sigma_t^2}}\exp\left(-\frac{(r_t-\mu_t)^2}{2\sigma_t^2}\right)\right. \qquad (9)\\ &\qquad \left. + \frac{\lambda}{\sqrt{\sigma_t^2+\delta^2}}\exp\left(-\frac{(r_t-\mu_t-\tau)^2}{2(\sigma_t^2+\delta^2)}\right)\right].\end{aligned}$$

As noted by Vlaar (1994), the Pearson goodness-of fit test cannot be applied on standardized residuals in such a framework because the *iid* assumption is no longer satisfied. Palm and Vlaar (1997) redefine the sorting mechanism of the residuals for the Pearson tests and suggest the use of normalized residuals defined as

$$z_t = F^{-1}\left[(1-\lambda)F(\frac{r_t-\mu_t}{\sigma_t}) + \lambda F(\frac{r_t-\mu_t-\tau}{\sigma_t+\delta})\right], \qquad (10)$$

where $F^{-1}()$ and $F()$ are the quintile function and the cumulative distribution function of the standard normal density, respectively.

Table 6 reports the estimation results for different specifications of (8). Following Beine and Laurent (2003), the ARMA and GARCH orders are selected by relying on the Schwarz Bayesian Information Criterion, which is known for leading to a parsimonious specification. Following this criterion, the specification selected is ARMAX(1,0)-GARCH(1,1). The results are not reported to save space but are nonetheless available upon request.

TABLE 6 ABOUT HERE

In Table 6, Model 1 represents a standard GARCH model with conditional Gaussian innovations which is obtained by imposing the parameter restriction $\lambda = 0$ to (8) on all the data available, i.e., from April 22, 2005 to May 31, 2013. The fundamentals for Phase 2 EUA prices that are found significant are consistent with the previous literature (see Creti et al. 2012).

In Model 2, we consider the same specification used in Model 1 but in the BMN framework. The likelihood ratio test (LR) favors this model over Model 1, i.e., the BMN is not rejected. Furthermore, in Model 1, the sum of the variance coefficients a and b is greater than one such that the variance exhibits explosive sample paths, which is no longer the case, however, when we explicitly account for the jump component in Models 2 to 4 using the BMN density. Thus, this process shows that the non-stationarity is spurious and is induced by the presence of additive level/variance jumps.[10]

[10]This is also the case if we compare Models 1 and 2 in the two subsamples. We do not report the results for purposes of brevity but they are available upon request.

The nature of the market has evolved since December 2007, which was the end of the trial phase. Even if agents expected the need for new generation capacity, power prices dropped drastically due to the decrease in demand that was driven by the European recession and the global financial crisis. The recession also had an impact on other sectors covered by the EU ETS, particularly in the cement sector. As a result, the price in the EU ETS decreased dramatically, and these types of changes can induce changes in market fundamentals. For this reason, we divide the sample into two subsamples before proceeding with our analysis. The first subsample studies the dynamics of EUA's Phase 2 prices traded from April 22, 2005 to December 31, 2007 (during Phase 1). The second subsample studies the dynamics of EUA's Phase 2 and Phase 3 prices traded in that same phase, i.e., from January 2, 2008 to May 31, 2013. The results of our estimation show that there are actually important differences between those subsamples. As in Creti et al. 2012, we find that only oil is weakly significant as a fundamental for EUA Phase 2 prices in the first subsample, i.e., between April 2005 and December 2007. This is explained by Kanen (2006), who posited that the price of oil was the major driver for the change in the price of natural gas and, in turn, that the price of oil has an impact on carbon trading prices. Finally, Benz and Trück (2008) suggest that, though the EUA prices during that period may show phases of specific price behavior due to fluctuations in production levels induced by shocks in fuel prices and extreme weather conditions, these sources of uncertainty have a mostly short-term impact and could induce price and volatility jumps rather than exhibit a strong relation with the underlying return process.

In the first subsample, the sign of the statistically significant coefficients associated with fundamentals are consistent with results in the literature (see for example Alberlola et al., 2008 and Mansanet-Bataller et al., 2007). Regarding the second subsample, to our knowledge, there is no study that analyzes the impact of fuel prices on the CO_2 price individually.[11] It is notable that, first, the sign of the coefficient associated with the gas relative price change is possibly determined to a large extent by the massive spike in natural gas prices (and its associated variability) that was experienced at the beginning of the sample. Second, contrary to the first subsample, during the second subsample, natural gas was cheaper than coal most of the time, which indicates that natural gas is no longer used as a substitute for coal but has become the preferred source for energy generation. This phenomenon explains the negative marginal impact: natural gas is less polluting than coal so when used as a substitute (as in the first subsample), its sign is positive. Nonetheless, natuaral gas is still a polluting input. Thus, when used (almost) exclusively as source for energy generation its sign becomes negative. That is, ceteris paribus, as the price of gas increases, its use decreases, which leads to decreased demand for permits that then induces a reduction in the CO_2 price.

Regarding the use of BMN, the advantage is striking. All parameters of the BMN are significant with the exception of the jump size (τ). As we have seen from Table 6, level outliers, though characterized by a large absolute value, show opposite signs. Since τ represents the average size of level outliers, the result suggests that a single parameter might not be sufficient to capture the sign of the level outliers because they tend to compensate, on average. The skewness parameter (b_3) that is associated with this specification is close to zero and insignificant, though the

[11] Differently from the individual analysis of fuel inputs we use herein, Creti et al. (2012) include explicitly fuel switching as an explanatory variable.

normalized residuals still exhibit some excess kurtosis (b_4). It is notable that even if the null of no excess kurtosis is rejected, the use of the BMN induces an important decrease in the excess kurtosis of the residuals compared with the results of the standard GARCH model with normally distributed errors: the coefficient b_4 reduces from 5.05 (Model 1) to 0.47 (Model 2). The Pearson goodness-of-fit test does not reject the BMN in Model 2 at the 5% nominal level. Finally, it is notable that, comparing Model 2 for the first subsample with Model 2 or the subsample beginning in January 2008, we see that jumps in this last case are less frequent, which may be explained by the development of the market moving closer to functioning as a financial market.

Although the BMN in (8) outperforms the standard GARCH-normal approach, assuming a constant jump probability specification yields few economic insights. In fact, according to recent literature, we might argue that these jumps may be due to changes in production resulting from shocks in fuel prices or by changes in the regulatory environment, but we cannot explicitly test these events' impact on the jump probability. Furthermore, despite the use of the BMN, normalized residuals still exhibit excess kurtosis (b_4). In fact, in all specifications, the statistics for excess kurtosis are found to be significant at the 5% level. In this regard, Beine and Laurent (2003) show that a BMN may fail in specifically accounting for excess kurtosis and they call for either a better specification of the conditional mean and variance, or for further flexibility in the distribution. We will pursue the latter option through the introduction of a time-varying jump probability as a function of a constant and a set of exogenous variables (x_{it-1}) related to the jump occurrence, which allows us to specifically test which are the determinants of outliers. The specification for λ_t in (7) is now substituted by:

$$\lambda_t = 1 - (1 + \exp(\gamma_0 + \Sigma_i \gamma_i x_{it-1}))^{-1} \tag{11}$$

which ensures $0 < \lambda_t < 1 \; \forall t$.

TABLE 7 ABOUT HERE

We identify two potential candidates as drivers of the shifts between regimes: *(i)* the daily relative change in the volume of transactions and *(ii)* changes in the regulatory environment caused by the European Commission's disclosure information on the EU ETS supply for Phase 2 and 3. Table 7 reports results for the specification (8)-(11). In Model 3, we let the jump probability depend on past realizations of the log-differential of the daily trading volume. As before we split the sample into two subsamples at January 1, 2008. The daily relative change in the volume is found to significantly affect the jump probability before January 2008 but not from January 2008 on. Such a result can be explained with the help of Tables 2 and 3: the mean of the relative change in the volume is larger in the first subsample and, most importantly, the standard deviation is much larger, which indicates that relative changes in volume were more important in the first subsample, when the market was less developed. Contributions on the relationship between volume of trade and jumps have been made by Gabaix *et al.* (2006) and Milunovich and Joyeux (2010), among others. These authors emphasize that the concentration of the market among a few leading players, the relatively low number of market transactions, the lack of transparency and therefore the discontinuous flow of information available during the initial phase of the EU ETS, played a dominant role. Furthermore, during that period, long-term futures contracts were traded in a relatively illiquid market

(Milunovich and Joyeux, 2010). Gabaix *et al.* (2006) shows that significant spikes in returns can be motivated by trades placed by large investors in relatively illiquid markets, even in the absence of important news about market fundamentals. Thus, it is natural to argue that, before January 2008, large incoming volumes reflecting sudden shifts in supply and/or demand, which in turn provoked a daily relative change in volume, dramatically affected the price of permits (either positively or negatively) and increased the variability in such prices. We find that an increase in the volume does not significantly affect the level of daily returns – although it induces a substantial increase in the return's variance during this period – which indicates that the price is likely to move widely the day following a large and positive fluctuation in the volume. The former effect is captured by the large estimate of δ^2. As from January 2008, the market shows signs of developement. Indeed, large fluctuations in the volume do no longer destabilize the market, i.e., the daily relative change in volume does not affect the likelihood of being in a high volatility regime.

Model 3 shows that, during the trial period (i.e., before January 2008), the probability of being in the high volatility regime varies between 0.45 and 0, with an average probability of 0.044. This value is consistent with the constant jump probability associated with Model 2 during the same subsample ($\lambda = 0.038$) in Table 6. Figure 2(a) depicts the evolution of the probability associated with the high volatility regime as a function of time for Model 3 before January 2008, while Figure 2(b) shows the dynamics for r_{vol} during the same period. The introduction of a time-varying probability as a function of the volume of contracts traded improves the fit of the model for this subsample.

FIGURE 2 ABOUT HERE

In Model 4 we consider the impact on the jump probability of the announcements made by the European Commission related to supply in the EU ETS. We find that announcements have substantial consequences on short-term price dynamics and the volatility level of EUAs because they significantly affect the jump probability in both subsamples. With respect to the announcements released before January 2008, because the adopted NAPs are substantially more restrictive than the national emission targets originally proposed by the member states (see Table 4 for details), the unexpected relative scarcity of EUAs for Phase 2 explains the large increase in the jump probability that was induced by the announcements.

Figure 3(a) reports the probability associated with the high volatility regime as a function of time, whereas Figure 3(b) shows the marginal contribution to the jump probability (λ_t) of the NAPs announcements for Model 4 before January 2008 (*i.e.* $\lambda_t(\gamma_0 + \gamma_{NAP} D_{NAP,t} + \gamma_{vol} r_{vol,t-1}) - \lambda_t(\gamma_0 + \gamma_{vol} r_{vol,t-1})$). The probability of being in the high volatility regime in this subsample varies between 0.57 and 0.005, with an average jump probability of 0.06. The average marginal contribution to the jump probability of the announcement in this subsample is 24% which is well above the average probability observed when there is no announcement (7.8%). Instead, in the second subsample (after January 2008), the contribution to the jump probability is 14% at most. Again, this shows market evolution compared with the previous subsample. The crucial role of changes in the regulatory framework or other policy issues appears clear when comparing Figure 2(a) with Figure 3(a). Changes in policy directives or in the regulatory environment may affect the short-run dynamics of EUA price and volatility, and in particular, our result suggests that announcements concerning the NAPs induce jumps and increase volatility in this subsample.

We have tested the independence between $r_{vol,t-1}$ and $D_{NAP,t}$ using the point biserial correlation coefficient. The null of no correlation cannot be rejected at standard significance levels.

FIGURE 3 ABOUT HERE

From January 2008 on, announcements of the EC still have a destabilizing effect. Figure 4(a) reports the probability associated with the high volatility regime as a function of time, whereas Figure 4(b) shows the marginal contribution to the jump probability (λ_t) of the NAPs announcements for Model 4 after January 2008. Model 4 in this subsample shows that the average jump probability is 0.015, which is much lower than in the subsample before January 2008. However, the probability of being in the high volatility regime in this subsample only varies between 0.19 and 0.

FIGURE 4 ABOUT HERE

5. CONCLUSION

In this paper, we examine the EUA Phase 2 and Phase 3 futures prices and volatility dynamics, and distinguish the EU ETS trial period running from April 2005 to December 2007, on the one hand, and the period corresponding to the Kyoto Protocol commitment period (which coincides with Phase 2) and Phase 3, on the other hand. This distinction allows us (i) to investigate if there have been any significant changes in the price and volatility dynamics after the EU ETS trial phase and (ii) to consider Phase 2 and Phase 3 prices, which are the most representative European carbon prices. An adequate assessment of short-term price and volatility dynamics represents a crucial issue in the EU ETS because accurately measuring and evaluating market risk is crucial for portfolio management and hedging in a market that is becoming more complex. We first model returns within a standard ARMAX-GARCH framework with normally distributed errors and show that the standard approach is not adequate because the distributional assumption is unable to properly account for excess skewness and kurtosis in the return series. In addition, we observe that the presence of outliers is the primary cause of the rejection of the Gaussianity assumption. To account for the presence of outliers, we combine the underlying price process with an additive stochastic jump component. The resulting distribution, a mixture of Gaussians, allows for endogenously determined jumps in the return process. The mixing law that we select for the mixture of densities is that of Bernoulli. Each individual distribution in the mixture can then be interpreted as a different regime, *e.g.*, a "continuous component" and/or a "jump", whereas the mixing law gives the probabilities of each regime. We find that a two-regime model based on a Bernoulli Mixture of Normals proves adequate to fit the data and clearly outperforms the standard approach.

The determinants and the occurrence of the jumps are further investigated by introducing a time-varying jump probability explained by the daily relative change in the volume of transactions and the change in the regulatory environment induced by the announcements of the European Commission. This approach is appealing because it provides useful insights regarding the occurrence of jumps and their economic interpretation.

We find that large incoming volumes have a destabilizing effect and translate into sudden and large volatility movements before January 2008 but not after. This result is consistent with the findings in the recent literature showing that the EU ETS during the trial period represented a relatively illiquid market concentrated among few leading players, in which the lack of transparency and the discontinuous flow of information available played a dominant role. From January 2008 on, the market has greatly developed both in terms of number of transactions and in terms of the number of participants. In fact, volatility estimates are beginning to approach estimates found in financial markets.

Additionally, the European Commission announcements have substantial consequences on the short-run dynamics of Phase 2 and Phase 3 EUA prices and volatilities both during the period running from April 2005 to December 2007 and from January 2008 on. In particular, our results suggest that they induce jumps in the process and increase volatility. The instability following the announcements for Phase 2 NAPs before January 2008 can be explained by the unexpected relative scarcity of EUAs for the second phase. The adopted NAPs were, in fact, substantially more restrictive than the initial targets proposed by each member state. The announcements regarding permit auctions and the cap for Phase 3 are also significant because they have an impact on the global supply for Phase 2 and Phase 3.

The previous result suggests that the regulatory environment, and thus the mechanism of release of new information, plays an important role for market stability. Such stability is needed to give the right incentives for environmental innovation and pollution reduction.

In general, it is desirable to provide agents with all the information available either with respect to market conditions, regulatory changes or modifications in the market design. On one hand, in the quest for transparency, stability and market efficiency, the authority generally releases all the information the moment it becomes available. On the other hand, it may be the case that the release of information by the authority generates instability by itself, which offsets the "stabilizing" intent of such information release. The previous result suggests that, even if the impact of the announcements related to the supply of the EU ETS has diminished considerably since January 2008, the authority still faces a trade-off between providing information effectively and promoting market stability.

REFERENCES

[1] Alberola, E., Chevallier, J., and Cheze, B., (2008), Price drivers and structural breaks in European carbon prices 2005-2007, Energy Policy, 36, 787-797.

[2] Alexander, C., (2004), Normal mixture diffusion with uncertain volatility: modelling short and long volatility smile effects, Journal of Banking and Finance, 28(12), 2957-2980.

[3] Alexander, C. and Lazar, E., (2006), Normal mixture garch(1,1): Applications to exchange rate modelling, Journal of Applied Econometrics, 21, 307-336.

[4] Beine, M. and Laurent, S., (2003), Central bank interventions and jumps in double long memory models of daily exchange rates, Journal of Empirical Finance, 10(5), 641-660.

[5] Benz, E. and Trück, S., (2009), Modeling the price dynamics of CO_2 emission allowances, Energy Economics, 31, 4–15.

[6] Bollerslev, T., (1986), Generalized autoregressive conditional heteroskedasticity, Journal of Econometrics, 31(3), 307-327.

[7] Bollerslev, T. and Wooldridge, J.M., (1992), Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, Econometric Reviews, 11(2), 143-172.

[8] Brännäs, K. and Nordman, N., (2003), Conditional skewness modelling for stock returns, Applied Economics Letters, 10, 725-728.

[9] Brock, A., Dechert, W.D. and Scheinkman, J.A., (1996), A test for independence based on the correlation dimension, Econometric Reviews, 15(3), 197-235.

[10] Bunn, D.W. and Fezzi, C., (2009), Structural Interactions of European carbon trading and energy prices, Journal of Energy Markets 4(2), 53-69.

[11] Chesney, M. and Taschini, L., (2012), The endogenous price dynamics of emission allowances and an application to CO_2 option pricing, Applied Mathematical Finance, 19(5),447-475.

[12] Chevallier, J., Le Pen, Y. and Sevi, B., (2011), Options introduction and volatility in the EU ETS, Resource and Energy Economics, 33(4), 855-880.

[13] Convery, F.J. and Redmond, L., (2007), Market and price developements in the European Union Emissions Trading Scheme, Review of Environmental Economics and Policy, 1(1), 88–111.

[14] Creti, A., Jouvet, P-A., Mignon, V. (2012), Carbon price drivers: Phase I versus Phase II equilibrium?, Energy Economics, 34, 327-334.

[15] Doornik, J.A. and Ooms, M., (2005), Outlier detection in GARCH models, Tinbergen Institute Discussion Paper No. 2005-092/4, Tinbergen.

[16] Ellerman, A.D. and Joskow, P.L., (2008), The European Union's Emissions Trading System in perspective, Pew Center on Global Climate Change.

[17] Ellerman, A.D. and Buchner, B.K., (2007), The European Union Emissions Trading Scheme: origins, allocation, and early results. Review of Environmental Economics and Policy, 1, 66–87.

[18] Gabaix, X., Gopikrishnan, P., Plerou, V. and Stanley, H.E., (2006), Institutional investors and stock market volatility, The Quarterly Journal of Economics, 121(2), 461-504.

[19] Haas, M., Mittnik, S., and Paolella, M.S., (2004), Mixed normal conditional heteroskedasticity, Journal of Financial Econometrics, 2(2), 211-250.

[20] Hansen, B. E., (1994), Autoregressive conditional density estimation, International Economic Review, 35, 705-730.

[21] Harvey, C. R. and Siddique, A., (1999), Autoregressive conditional skewness, Journal of Financial and Quantitative Analysis, 34(4), 465-487.

[22] Kanen, J.L.M., (2006) Carbon Trading and Pricing, Environmental Finance Publications, London.

[23] Kanzler, L., (1998), BDS: MATLAB module to calculate Brock, Dechert & Scheinkman test for independence, Statistical Software Components T871803, Boston College.

[24] Kaufmann, R. K. and Ullman, B., (2009), Oil prices, speculation, and fundamentals: Interpreting causal relations among spot and futures prices, Energy Economics 31(4), 550-558.

[25] Mansanet-Bataller, M., Pardo, A. and Valor, E., (2007), CO_2 prices, energy and weather, The Energy Journal, 28, 73-92.

[26] Milunovich, G. and Joyeux, R., (2010), Testing market efficiency in EU carbon futures markets, Applied Financial Economics 20(10), 803-809.

[27] Palm, F.C. and Vlaar, P.J.G., (1997), Simple diagnostic procedures for modelling financial time series, Allegemeines Statistisches Archiv, 81, 85-101.

[28] Paolella, M. S. and Taschini, L., (2008), An econometric analysis of emission trading allowances, Journal of Banking & Finance, 32(10), 2022-2032.

[29] Rockinger, M. and Jondeau, E., (2002), Entropy densities with an application to autoregressive conditional skewness and kurtosis, Journal of Econometrics, 106, 119-142.

[30] Skjærseth, J.B. and Wettestad, J., (2008), EU emissions trading: initiation, decision-making and implementation, Aldershot, Ashgate Publishing.

[31] Seifert, J., Uhrig-Homburg, M., Wagner, M., (2008), Dynamic behavior of CO_2 spot prices, Journal of Environmental Economics and Management, 56 (2), 180–194.

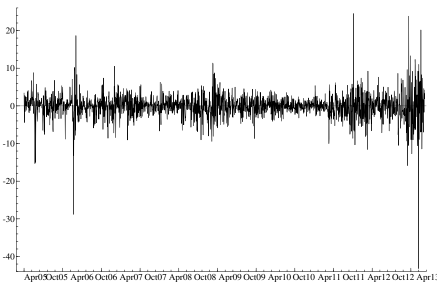
[32] Vlaar, P.J.G., (1994), Exchange rates and risk premia within the European Monetary System, PhD Thesis, Rijksuniversiteit Limburg, Maastricht.

[33] Vlaar, P.J.G. and Palm, F.C., (1993), The message in weekly exchange rates in the European Monetary System: mean reversion, conditional heteroskedasticity and jumps, Journal of Business and Economic Statistics, 11, 351-360.

[34] Weiss, A.A., (1986), Asymptotic theory for ARCH models: estimation and testing, Econometric Theory, 2, 107-131.

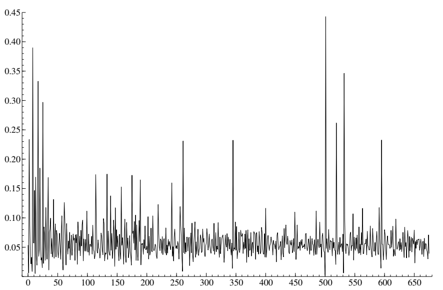
6. FIGURES

(a) EU ETS futures price

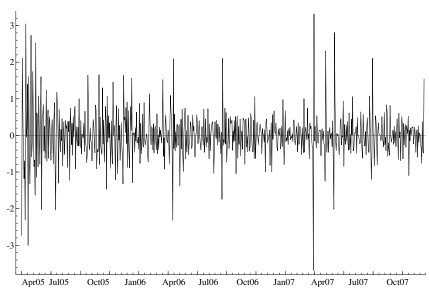


(b) EU ETS returns

FIG. 1 EU ETS prices of future contracts and returns on futures price

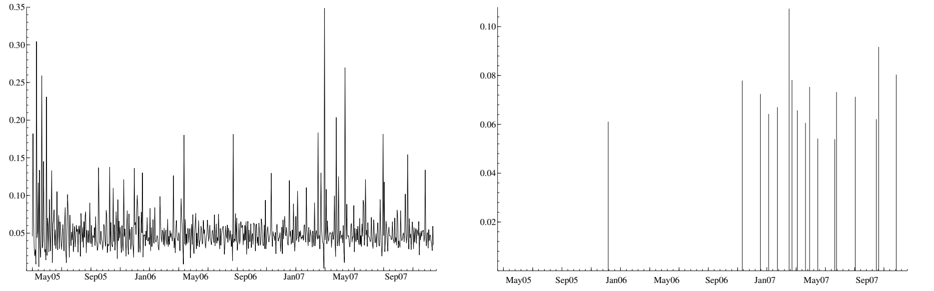


(a) Time varying jump probability



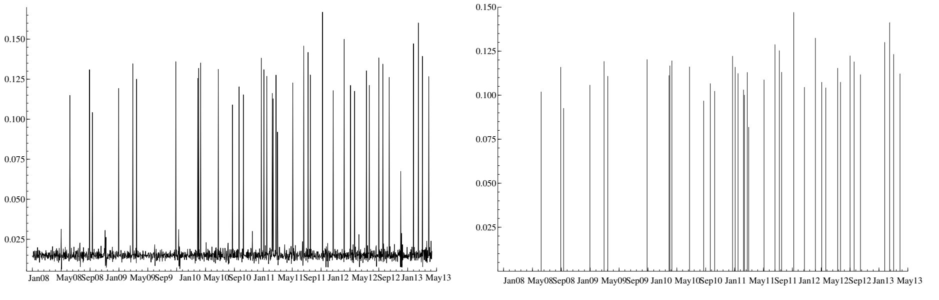
(b) Relative change in volume (r_{vol})

FIG. 2 Time varying jump probability and transaction volume (04/05-12/07)



(a) Time varying jump probability (b) Marginal contribution of announcements

FIG. 3 Time varying jump probability and Marginal contribution of announcements (04/05-12/07)



(a) Time varying jump probability (b) Marginal contribution of announcements

FIG. 4 Time varying jump probability and Marginal contribution of announcements (01/08-06/13)

7. TABLES

Variable	min	mean	max	std dev	sk	ku
Estimation sample: 22/04/05-31/05/13 (2072 observations)						
r_{EUA}	-0.4321	-0.0007	0.2452	0.0328	-1.1061	25.2565
r_{vol}	-4.0587	0.0026	3.3207	0.5421	-0.1088	10.4415
r_{gas}	-0.2603	0.0003	0.4769	0.0409	2.8372	27.2020
r_{coal}	-0.3164	0.0001	0.1630	0.0201	-2.2352	42.0526
r_{elec}	-0.4636	0.0000	0.4390	0.0187	-0.6205	333.600
r_{oil}	-0.1165	0.0003	0.1399	0.0211	-0.0751	6.8252

TABLE 1
Summary statistics in full sample

Variable	min	mean	max	std dev	sk	ku
Estimation sample: 22/04/05-31/12/07 (686 observations)						
r_{EUA}	-0.2882	0.0004	0.1865	0.0302	-1.4618	19.3538
r_{vol}	-3.6835	0.0032	3.3207	0.6611	-0.0009	9.1452
r_{gas}	-0.2606	0.0007	0.4769	0.0558	2.4521	17.8157
r_{coal}	-0.1565	0.0008	0.1630	0.0163	0.5902	33.2990
r_{elec}	-0.0822	0.0008	0.0566	0.0108	-0.8240	12.2683
r_{oil}	-0.0580	0.0006	0.0682	0.0176	0.0589	3.0608

TABLE 2
Summary statistics in the first subsample

Variable	min	mean	max	std dev	sk	ku
Estimation sample: 01/01/08-31/05/13 (1387 observations)						
r_{EUA}	-0.4321	-0.0012	0.2452	0.0340	-0.9681	26.7042
r_{vol}	-4.0587	0.0023	2.2463	0.4725	-0.2461	9.7350
r_{gas}	-0.1220	0.0000	0.3600	0.0310	2.6279	30.5287
r_{coal}	-0.3167	-0.0002	0.1216	0.0218	-2.7450	40.6008
r_{elec}	-0.4630	-0.0003	0.4391	0.0216	-0.5162	281.6058
r_{oil}	-0.1165	0.0001	0.1399	0.0227	-0.0961	7.1354

TABLE 3
Summary statistics in the second subsample

Date ($D_{news} = 1$)	State	NAP Phase I	2005 emissions	NAP Phase II (% of proposed)
09/01/06	Publication of guidelines for NAP approval			
29/11/06	Germany	499	474	453.1 (94.0%)
	Greece	74.4	71.3	69.1 (91.5%)
	Malta	2.9	1.98	2.1 (71.0%)
	UK	245.3	242.4	246.2 (100%)
16/01/07	Belgium	62.1	55.58	58.5 (92.4%)
	Netherlands	95.3	80.35	85.8 (94.9%)
05/02/07	Slovenia	8.8	8.7	8.3 (100%)
26/02/07	Spain	174.4	182.9	152.3 (99.7%)
26/03/07	Czech Rep.	97.6	82.5	86.8 (85.2%)
	France	156.5	131.3	132.8 (100%)
	Poland	239.1	203.1	208.5 (73.3%)
02/04/07	Austria	33	33.4	30.7 (93.6%)
16/04/07	Hungary	31.3	26	26.9 (87.6%)
04/05/07	Estonia	19	12.62	12.72 (52.2%)
15/05/07	Italy	223.1	225.5	195.8 (93.7%)
04/06/07	Finland	45.5	33.1	37.6 (94.8%)
13/07/07	Ireland	22.3	22.4	22.3 (98.6%)
	Latvia	4.6	2.9	3.43 (44.5%)
	Lithuania	12.3	6.6	8.8 (53.0%)
	Luxembourg	3.4	2.6	2.5 (63.0%)
	Sweden	22.9	19.3	22.8 (90.5%)
18/07/07	Cyprus	5.7	5.1	5.48 (77.0%)
31/08/07	Denmark	33.5	26.5	24.5 (100%)
22/10/07	Portugal	38.9	36.4	34.8 (96.9%)
26/10/07	Bulgaria	42.3	40.6	42.3 (62.6%)
	Romania	74.8	70.8	75.9 (79.3%)
07/12/07	Slovakia	30.5	25.2	32.6 (78.9%)
Total		2298.5	2122.2	2082.7 (89.6%)

Source: European Climate Change Program press releases.

TABLE 4
EC's announcements from April 2005 to December 2007

Date ($D_{news} = 1$)	Description
08/07/08	Parlament votes on aviation inclusion
10/10/08	Directive of the Council on aviation inclusion
24/10/08	Inclusion of Aviation in ETS
15/05/09	Verified emissions 2008
04/06/09	Public consultation auctioning launched
01/04/10	80% Verified emissions
14/07/10	Member states back auctioning rules
21/09/10	Debate on aviation activities
22/10/10	Cap Phase 3 adopted by the Comission
12/11/10	Auctionin Regulation Phase 3
21/02/11	Common platform for auctioning defined
07/03/11	Historical emissions on aviation published
01/04/11	Verified emissions 2010
06/04/11	Aviation emission's legislation implementation
20/04/11	Comission publishes EEA list of aviation operators
13/07/11	120 millon allowances will be auctioned in 2012
26/09/11	Airlines free allocation rules aproved
06/10/11	Aviation rules compatible with international law
30/01/12	Registry activated for airline operators
22/03/12	Germany notifies opt-out auction plataform
25/04/12	Aproval of Germany's first Phase 3 auction plataform
15/05/12	Declined verified emissions 2011
11/07/12	Aproval of UK's first Phase 3 auction plataform
25/07/12	Retirement of permits to auction from 2013-2020
	Schedulle change for auctions Phase 3
10/09/12	EEX appointed as first common auction plataform
28/09/12	Preliminary auction calendar for 2012
30/10/12	2012 aucton calendar fixed for transitional comon platform
28/02/13	Pending procedures for aviation issuance of allowances
25/03/13	EEX contacted to delay aviation's auction
16/04/13	Parliament votes againts Comission's back-loading proposal
16/05/13	Allowance surplus doubled in 2012

Source: European Climate Change Program press releases.

TABLE 5
EC's announcements from January 2008 to May 2013

Param.	Model 1	Model 2	Model 2 B.01/08	Model 2 A.01/08
γ_0	–	-3.310^*	-3.232^*	-3.958^*
		(0.238)	(0.431)	(0.374)
τ	–	-2.257	-2.988	-2.079
		(1.217)	(2.566)	(2.553)
δ^2	–	56.653^*	60.726^*	106.839^*
		(7.709)	(18.538)	(25.124)
β_0	0.077^*	0.146^*	0.285^*	0.078
	(0.057)	(0.074)	(0.155)	(0.085)
β_1	0.058^*	0.073^*	0.124^*	0.046
	(0.024)	(0.023)	(0.044)	(0.024)
β_{gas}	-0.023^*	-0.027^*	0.005	-0.069^*
	(0.010)	(0.009)	(0.011)	(0.018)
β_{coal}	-0.007^*	-0.050^*	-0.034	-0.059^*
	(0.022)	(0.021)	(0.042)	(0.026)
β_{elec}	0.001	0.003	0.009	-0.002
	(0.008)	(0.008)	(0.010)	(0.014)
β_{oil}	0.039^*	0.023	0.108^*	-0.011
	(0.020)	(0.021)	(0.045)	(0.027)
β_{tmp_lo}	-0.146	-0.092	0.261	-0.144
	(0.253)	(0.210)	(0.349)	(0.220)
β_{tmp_hi}	0.072	0.123	-0.296	-0.147
	(0.227)	(0.206)	(0.378)	(0.237)
c	0.270^*	0.131^*	0.444^*	0.054^*
	(0.040)	(0.032)	(0.135)	(0.020)
a	0.217^*	0.127^*	0.132^*	0.090^*
	(0.015)	(0.014)	(0.030)	(0.013)
b	0.784^*	0.835^*	0.757^*	0.894^*
	(0.016)	(0.016)	(0.047)	(0.014)
mean λ	–	0.035	0.038	0.019
Freq.	–	29	26.34	53.37
# Jumps	–	73	26	26
# Obs	2072	2072	686	1386
LLF	-4960.55	-4876.5	-1591.4	-3264.7

	Stat	p-val	Stat	p-val	Stat	p-val	Stat	p-val
b_3	-0.544	0.00	-0.069	0.20	-0.075	0.42	-0.075	0.26
b_4	5.051	0.00	0.472	0.00	0.470	0.01	0.297	0.02
$BDS(6)$	-1.434	0.15	0.078	0.93	0.469	0.64	0.978	0.33
$P(30)$	99.004	0.00	51.340	0.00	40.21	0.00	31.07	0.01

Notes: Parameter standard errors in parentheses. * indicates significant at 10%. B.01/08 stands for ¨Before January 2008¨ and A.01/08 for ¨After January 2008¨.

TABLE 6
Benchmark model and BMN with constant jump probability

Param.	Model 3 B.01/08	Model 3 A.01/08	Model 4 B.01/08	Model 4 A.01/08
γ_0	-3.091^*	-3.958^*	-2.739^*	-4.194^*
	(0.419)	(0.378)	(0.370)	(0.426)
γ_{vol}	0.729^*	-0.173	2.041^*	-0.387
	(0.400)	(1.148)	(0.894)	(1.132)
γ_{news}	–	–	0.806^*	2.292^*
			(0.392)	(0.999)
τ	-1.682	-1.980	-0.682	-1.116
	(1.958)	(2.877)	(0.973)	(2.525)
δ^2	52.003^*	106.827^*	38.876^*	107.935^*
	(12.798)	(28.780)	(6.657)	(27.076)
β_0	0.246^*	0.072	0.213^*	0.059
	(0.151)	(0.087)	(0.132)	(0.444)
β_1	0.121^*	0.044^*	0.117^*	0.046^*
	(0.044)	(0.024)	(0.043)	(0.024)
β_{gas}	0.001	-0.069^*	0.007	-0.069^*
	(0.012)	(0.0018)	(0.012)	(0.018)
β_{coal}	-0.037	-0.061^*	-0.034	-0.061^*
	(0.040)	(0.026)	(0.042)	(0.026)
β_{elec}	0.008	-0.001	0.006	-0.001
	(0.009)	(0.013)	(0.009)	(0.013)
β_{oil}	0.094^*	-0.011	0.081^*	-0.011
	(0.045)	(0.027)	(0.044)	(0.027)
β_{tmp_lo}	0.256	-0.070	0.112	-0.080
	(0.346)	(0.231)	(0.362)	(0.231)
β_{tmp_hi}	-0.300	-0.188	-0.299	-0.214
	(0.367)	(0.262)	(0.341)	(0.263)
c	0.397^*	0.052^*	0.310^*	0.051^*
	(0.127)	(0.020)	(0.107)	(0.020)
a	0.128^*	0.089^*	0.122^*	0.088^*
	(0.030)	(0.013)	(0.029)	(0.012)
b	0.762^*	0.896^*	0.771^*	0.897^*
	(0.047)	(0.014)	(0.045)	(0.013)
mean λ	0.044	0.019	0.061	0.015
Freq.	23	53	17	67
# Jumps	30	26	42	21
# Obs	686	1386	686	1386
LLF	-1589.4	-3264.7	-1587.9	-3261.9

	Stat	p-val	Stat	p-val	Stat	p-val	Stat	p-val
b_3	-0.123	0.19	-0.083	0.21	-0.214	0.02	-0.078	0.24
b_4	0.440	0.02	0.292	0.03	0.557	0.00	0.258	0.04
$BDS(6)$	0.445	0.66	0.980	0.33	0.438	0.66	1.034	0.34
$P(30)$	34.700	0.00	24.653	0.04	32.34	0.00	25.13	0.02

Notes: Parameter standard errors in parentheses. * indicates significant at 10%
B.01/08 stands for ¨Before January 2008¨ and A.01/08 stands for ¨After January 2008¨

TABLE 7
Time varying jump probability

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