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Auctioning C02 Emission Allowances in Europe. A Time Series Analysis of Equilibrium Prices

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AUCTIONING $C0_2$ EMISSION ALLOWANCES IN EUROPE. A TIME SERIES ANALYSIS OF EQUILIBRIUM PRICES[1]

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Abstract

The purpose of this paper is to offer an analysis of the price behavior of Phase III (2013–2020) EU- ETS emission allowances of CO2, by focusing on the dynamics of daily auction equilibrium prices and on the changes of the volatility of the underlying stochastic process. The paper initially investigates the characteristics of equilibrium prices as they result from auction rules and bidders' behavior and uses them as a theoretical basis of the statistical hypothesis–common to the empirical literature active in this field– of a changing conditional variance of prices. Then, different versions of a GARCH model are employed to estimate both mean and variance equations of price dynamics and to evaluate what factors affect price volatility, recorded excess supply, and bidders' surplus. Brief policy considerations are also offered.

Keywords. EU-ETS emission auctions; Equilibrium prices volatility; GARCH

1. Introduction

The creation in 2005 of the EU-wide CO_2 GHG (greenhouse gas) emission trading system, (EU-ETS from now on) represented a novelty in European environmental policy (EU, 2015; World Bank 2016). It partially replaced traditional tax and administrative forms of regulation (including *grandfathering*, i.e. giving polluters permits in proportion to past pollution), with a *cap-and-trade* mechanism in which the right to emit a certain amount of CO_2 is a tradable and bankable commodity[2]. The system permits buying emissions allowances, i.e. permissions to emit one ton of carbon dioxide or carbon dioxide equivalent in a specified period. Allowances are assigned to participating installations and aircraft operators in the EU who bid for their acquisition. The auction *cap*, i.e. the maximum amount of GHG emissions allowed for allocation, operates in combination with a *trading* system. The latter allows participants that reduce their GHG emissions further than required, and consequently *bank* their unused permissions, to trade their excess allowances with other participants who have a shortage of allowances or to use them to cover their own future emissions. As borrowing is not allowed, permission to sell unused allowances is a means to increase the liquidity of the market. Unlimited banking was introduced in 2008.
The EU–ETS *cap-and-trade* auction system is designed as a competitive (i.e. single price) multiunit auction aiming at pursuing cost effective and economically efficient reductions of GHG emissions by producing price signals that should reflect the abatement costs as well as the scarcity of the allowances. Auction efficiency requires that

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[2] Vollebergh and Brink (2020) relate this European novelty to the previous US experience with the SO_2 cap-and-trade scheme of the 1990s (Burtraw and Szambelan, 2009). To date, the EU ETS has been the largest emissions trading scheme in the world (World Bank, 2019). Revenues from the allowance auctions are distributed to member states as "auction rights" according to a formula that is inversely, but loosely, related to national per-capita income (Ellerman 2010). At least 50% of revenues should be used for climate- and energy-related purposes

allowances should go to bidders who value them most, i.e. those who have the highest marginal cost of reducing emissions. Participants with lower marginal cost and higher elasticity of substitution between polluting and non-polluting means of production would rather choose other ways to abate their emissions and comply with environmental regulation, e.g. by production optimization and investment in low carbon technology. On the contrary, buying allowances at the auction is supposed to ensure a quick, simple and least bureaucratic way to permit those who face dissimilar technological and economic constraints to carry on profitably with polluting production and continue business as usual.

Auctioning has progressively become the default method for allocating allowances, not only in Europe. Yet, according to the official EU website, EU-ETS has become the world's first major carbon market and observers estimate that it has contributed to the decrease of the overall trend in carbon emissions within the EU–ETS sectors[3] –mainly in the electricity sector[4]– although it is yet unclear to what extent. EU-ETS operates in all EU countries plus Iceland, Liechtenstein, Norway and the UK. It limits emissions from more than 11,000 heavy energy-using installations (power stations and industrial plants) and airlines operating between these countries and covers around 45% of the EU's GHG emissions. Many sectors and gases are included[5] and 300 million allowances are set aside in the New Entrants Reserve (NER) to fund the deployment of innovative, renewable energy technologies and carbon capture and storage through the NER 300 program[6].

Since 2005, the implementation of the EU–ETS system has gone through different trading periods (officially called *Phases*) and auction rules have been somehow modified from one phase to the next. In the first and second phases (2005–2007 and 2008–2012, respectively), the average ratio between allowances demanded and the total available allowances (called *Cover Ratio* and actually measured as the ratio between the bid volume and the available volume in the auction) was about 1 and 4% respectively. It indicated the realization of serious imbalances of allowances. Indeed, during the period 2009–2013, an enormous oversupply occurred and the allowance market built up a huge "bank" of allowances having an infinite lifetime. Note that in 2013–2014 the bank was even larger than a whole year of allowance supply (Vollebergh and Brink, 2020, 3). The review of the EU–ETS rules and the launch of the third phase (2013–2020) lead to some important changes. The number of bidders increased with respect to previous periods and the *Cover Ratio* reduced from 4 times to *just* twice. This might indicate that the new rules permitted a reduction of the imbalances and generated a tendency towards long run equilibrium, a result not achieved in previous phases. With the linear reduction factor adopted in the revised EU–ETS Directive of 2018, the supply of allowances is expected to be zero in 2057. Since the decreasing cap implies that the cap will become more and more restrictive, banking helps to smooth the impact of the restrictions as it provides for intertemporal flexibility in the trade of allowances. Towards the end of phase 3 (January 2019), a Market Stabilizing Reserve (MSR) system was introduced to further reduce excess supply phenomena.

[3] The reduction program is the following. By 2020: 20% below 1990 GHG levels. By 2030: at least 40% below 1990 GHG levels. By 2050: EU leaders have committed to reaching climate neutrality by mid-century.

[4] EU-ETS may also be credited to have increased the cost of carbon intensive production and contribute to a short run fuel switching from coal to natural gas (Delarue et al., 2010) not to mention a change in long-run expectations of returns on investments in carbon intensive projects.

[5] The system covers the following sectors and gases, focusing on emissions that can be measured, reported and verified with a high level of accuracy. Carbon dioxide (CO_2) from: a) power and heat generation; b) energy-intensive industry sectors including oil refineries, steel works and production of iron, aluminum, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals; commercial aviation; nitrous oxide (N_2O) from production of nitric, adipic and glyoxylic acids and glyoxalin perfluorocarbons (PFCs) from aluminum production. Participation in the EU ETS is mandatory for companies operating in the above sectors but in some cases only plants above a certain size are included. Moreover, certain small installations can be excluded if governments put in place fiscal or other measures that will cut their emissions by an equivalent amount.

[6] NER 300 is a funding program pooling together about 2 billion euros for innovative low-carbon technology, focusing on the demonstration of environmentally safe Carbon Capture and Storage (CCS) and innovative renewable energy technologies on a commercial scale within the EU.

The purpose of this paper is to analyze the equilibrium price behavior of Phase III of EU–ETS auctions focusing of the properties of the underlying stochastic process and to evaluate the effects on this dynamic of the above-mentioned measures introduced at the beginning and towards the end of Phase III to reduce excess supply and make the market more efficient. More specifically, after describing the main characteristics of the EU-ETS auction mechanism, the paper analyses in section 2 the properties of the equilibrium prices realized at each auction round as they are generated by optimal bid strategies. In doing so, the paper analyses the link between equilibrium prices and bidders' valuation with regard to both winning and non-winning bidders. Then, in section 3, the paper analyzes the stationarity property of the de-trended prices series and evaluates if their mean, variance and covariance follow some discernible trend or if meander without constant long-run mean or variance. Considerations derived from the properties of optimal bid functions of section 2 and results of section 3 suggest that the variance of the auction equilibrium price is not constant and that modeling the returns of emission allowances should depart from random walk in order to capture characteristics like skewness, excess kurtosis and in particular different phases of volatility behavior. Section 4 contains all these estimation results. In section 5, different versions of a GARCH model are tested and different variance equations are estimated to analyze what factors affect price volatility and how the estimated volatility (the estimated conditional variance) has evolved over time. It is found that the number of successful bidders as well as the total monetary amount bid affect negatively, as expected on the basis of results obtained in section 2, the equilibrium price whereas the total number of bidders (winners and non-winners) and the cover ratio (interpretable as a measure of auction inefficiency) reduce volatility. On the contrary, the bid spread (the difference between maximum and minimum bid in each auction round) increases it. Predicted prices and availability of bid data permit the estimation of bidders' surplus (difference between willingness to pay and actual payment) realized during the entire Phase III (and the end of Phase II). The time path of the surplus is shown in section 6, where one can appreciate the sharp increase of the winners' surplus (generated by the informational rent given by bidders' private information on pollution technology) realized during the last part of Phase III. Conclusions are presented in section 7 where I emphasize the link constructed in this paper between the results of a theoretical bidding model and the statistical properties of the time series of equilibrium prices as a key element for the interpretation of the GARCH outcomes. Interpretations of the empirical results is also offered in terms of policy issues.

2. The EU-ETS auction mechanism

The EU-ETS is now in its third phase, which is significantly different from phases I and II[7]. In addition to the introduction of the above-mentioned linear reduction factor and MRS adjustment scheme, a single EU-wide cap on emissions replaced the previous system of national caps thereby aggregating isolated national allowance markets into a single European market. As a result, the mechanism fix with certainty the maximum quantity of GHG emissions for the period of time over which system caps are set. In ETS auctions, bidders submit their bids during one given bidding window/round (Day) without seeing bids submitted by other bidders complying with the following rules:

i) Bidders present Sealed Single Round Secret Bids knowing that their bids will be sorted in descending order of the price bid (price offered for ton of equivalent CO_2);
ii) Bid volumes are added horizontally, starting with the highest price bid.
iii) The price component of the bid determines the position in the decreasing merit order (demand schedule) of the bidders. Clearly, since each bidder can propose more than one price bid –each specifying the price she/he is willing to pay and the amount of allowance for which she/he bids that price– a single bidder may occupy more than one position in the above merit order depending on the level of the price bids she/he has submitted.

[7] Detailed description of allocation mechanisms can be found in EU (2015). For updated information see Ellerman et al. (2016) and Vollebergh and Brink (2020).

iv) The price at which the sum of the volumes' bids matches or exceeds the volume of allowances auctioned determines the auction-clearing price that will be paid by all successful bidders, i.e. bidders with a price bid higher than or equal to the equilibrium price.
v) No "*Safety Valve*" (ceiling instrument limiting price level) is included.
vi) Borrowing of allowances is not allowed.
vii) Tied bids will be sorted through random selection according to an algorithm.
viii) All bids with a price higher than (or equal to) the auction-clearing price are successful and receive the requested allowances.
vii) Partial execution of orders may be possible for the last successful bid matching the auction-clearing price.

Each successful bidder will pay the same auction-clearing price for each allowance regardless of the price bid she submitted. This implies that allowances are sold at a competitive price, which is to some extent equivalent to the system marginal price of bulk electricity auctions (Parisio et al., 2003; Bosco et al, 2010, Bosco et al, 2016) where an equivalent rule determines the payment received by all dispatched generators in a wholesale pool.
In any auction, it is crucial to define the items being auctioned. Crampton and Kerr (2002) originally stressed that with carbon permits this is a simple matter. Each permit is for one metric ton of carbon usage and with "revenue recycling" polluters effectively buy the right to pollute from the public. Hence, each round of (Phase III) ETS auction can be modelled as a simultaneous uniform price auction for a divisible item given by the total TONs allowance of CO_2 *(*call it Q^C), which can be partitioned in subunits of possible different size. This makes the auction similar to a share auction mechanism (Wilson, 1979) where each bidder aims at *winning* a set of subunits. I assume that ach bidder j receives private signals about the value of the allowances, v_j. This value depends upon her/his ongoing production technology (a private information) and can be understood as the opportunity cost of the allowance, i.e. as the cost of replacing nonpolluting for polluting means of production through a costly abatement activity (Leiby et al., 2001). Bidders know that it is drawn from a commonly known continuous function $F(v)$ with finite density $f(v)$ and the support $[\underline{v}, \bar{v}]$. I assume that while $F(.)$ is common knowledge the realization of v_i is a private information, since it depends upon the above individual opportunity cost of alternative and idiosyncratic technical innovation. This justify the assumption that v is an *i.i.d.* random variable and that the IPV hypothesis applies.
Adapting from Donald et al. (2006, 1230) I assume that a known number of potential bidders N may bid for $H \leq Q^C$ units of allowances and denote v_j the vector of ordered valuations of bidder j. Under the hypothesis of diminishing marginal productivity of the allowances for each user, one may assume that $v^j = v_1^j > v_2^j > \cdots > v_{T \leq H}^j$ where the subscript indicates each unit of allowance requested by bidder j[8]. Recalling that $F(v)$ is the cumulative distribution of valuations, the order statistics of *all* valuations of the N potential bidders is

$$v_{1:N} < v_{2:N} < \cdots < v_{I-1:N} < v_{I:N} < v_{I+1:N} < \cdots < v_{N:N}$$

with valuation ranked in increasing order. Since the auction is not a *singleton-demand* auction (Milgrom, 2004, 31) where buyers want only a single object, a bidder j can occupy more than one position in the sequence of order statistics. The *reversed decreasing order* forms a sort of marginal valuation function of allowances (unobserved total true willingness to pay for the allowances of all bidders) in which each bidder j may occupy more than one position according to her and other bidders' valuation of each allowance unit.

In what follows, we focus on equilibrium bid/price and auction efficiency.

[8] This assumption corresponds to the diminishing marginal utility assumed in multi-unit auctions by Ausubel et al. (2014, 1371).

Definition 1 Bidder gain

Two elements determine bidders' utility. The first element is the above private valuation as it is determined by the opportunity cost of the adoption of alternative nonpolluting technologies. This is the value of each TON of CO_2 per unit of produced output and it is a pure private information. In what follows this variable is denoted as v_i^j(the value assigned to unit *i* by bidder *j*) and the total volume of allowances won by bidder *j* is $Q^j = \sum_{i=1}^{H} Q_i^j$.
The second element affecting utility is the value of the banked allowances, i.e. unused TONs of CO_2 bought at some previous auction price $\overline{p}$, which the bidder expects to resell at some future equilibrium price. Calling Q_i^j each allowance *i* won by bidder *j* and K^j the stock of banked allowances already in her/his portfolio (a value always non negative because borrowing is not allowed), we can write the ex-post utility of bidder *j* after each auction round is concluded (i.e. once p^* is determined) as follows

$$U_j\left(Q_i^j, K_{ji}\right) = \sum_{i=1}^{H}\left(v_i^j - p^*\right)Q_i^j + (p^* - \overline{p})K^j$$

where *H* is the number of allowances won by bidder *i* and $\overline{p}$ is for simplicity an average of past allowances price. Then, the last term can be either positive or negative. Implicit differentiation of ex-post maximum utility shows that with $(p^* - \overline{p}) > 0$ a high level of the bank negatively affects the equilibrium price.

Definition 2: Efficiency

I assume that having observed her signal bidder *i* submits a set of Bayesian-Nash Equilibrium monotonous continuous increasing bid functions, each specified as $b_j\left(Q_i^j, v_i\right): [0, Q^C] \rightarrow [0, \overline{B}]$ where the upper limit is common to all bidders and may be set equal to the cap. Each function is the value bid for any unit $Q_i \in Q^C$ the bidder *j* wants to acquire. Assume that the auction ends with $I < N$ winners where *N* is the set of all bidders, the cap

$$Q^C = Q^*(s) \equiv \left(Q^1, \dots, Q^j, \dots, Q^I\right)$$

is ex-post efficient if each subunit in which Q^C can be divided goes to the bidders who value them the most:

$$Q^*(s) = argmax_{\{Q_{1(s)},\dots,Q_{I(s)}\}}\left\{\sum_{j=1}^{I} U_j\left(Q_i^j(s)\right)\middle|\sum_{j=1}^{I}\sum_{i=1}^{H} Q_i^j(s) \le Q^C\right\} \tag{1}$$

Given the competitive auction format and assuming the bid function is invertible, the market-clearing price, which corresponds to the lowest accepted bid, is:

$$p^* = min\left\{p\middle|\sum_{j=1}^{I}\sum_{i=1}^{H} Q_i^j(s) \le Q^C \le Q^C\right\} = min\left\{p\middle|\sum_{j=1}^{I} b_j^{-1}(p|v_i) \le Q^C\right\} \tag{2}$$

As a result, each winner pays the total amount $P_j = p^* Q_j$, which implies that the total revenue generated by each auction is $R = p^* Q^C$ with the ratio $c = \sum_{j=1}^{N} b_j^{-1}\{p|s_j\} / \sum_{j=1}^{I} b_j^{-1}\{p|v_i\}$ indicating the excess demand of allowances realized at the equilibrium price, conventionally called by ETS as the *Cover Ratio* (a value that was invariably greater than one). As a result, one can also define efficiency as

$$min_{\{Q_{1(s)},\dots,Q_I(s)\}}\left\{1, \sum_{j=1}^{N} b_j^{-1}\{p|s_j\} / \sum_{j=1}^{I} b_j^{-1}\{p|v_i\}\middle|\sum_{j=1}^{I}\sum_{i=1}^{H} Q_i^j(s) \le Q^C\right\} \tag{3}$$

i.e. as the absence of excess demand (or as *c* = 1).

Definition 3: Equilibrium price and rent

If $b_j(.) = b_{I:N}(.)$ is the last accepted bidder, the equilibrium price, $p*$ can be related to valuations as follows

$$p^* = E[b(v_I, Q_I)|v_{I:N} > v_{I-1 \in N}] = E[v_{I-1:N}|v_{I:N} = V]$$

In words, the equilibrium price, corresponding to the last accepted bid, is a bid corresponding to the expected value of the highest valuation among all the remaining (N–I) bidders, i.e. the highest valuation existing among the non-winners when $\sum_{i=1}^{I} Q_i(p^*) = Q^C$conditional to fact that $v_{I:N} = V$. As a result, the density of the "marginal" bid in each auction t is

$$f_{(N-I+1:N)}\left(v_j | v_{N-I:N} = v_i\right) = \frac{[F(v_I^t|s_I^t, s_{-I}^t)]^{N-I-1} f\left(v_I^t|s_j^t, s_{-I}^t\right)}{[F(v_I^t|s_I^t, s_{-I}^t)]^{N-I}}$$

The conditional expected value of the equilibrium bid determining $p*$ (and corresponding to the valuation of the first rejected bidder I – 1 conditional upon v_j being the I*th* valuation) is

$$E\left[v_{N-(I+1):N}\right] = \mu_{N-(I+1):N} = \int_{\underline{v}}^{\overline{v}} v f_{(N-I-1:N)}\left(v_j | v_{N-(I-1):N} = v_h\right) dv$$

$$= (I-1) \int_{\underline{v}}^{\overline{v}} v \left[\frac{F(v_{I-1})}{F(v_I)}\right]^{I-2} \frac{f(v_{I-1})}{f(v_I)} dv$$

$$= E[p^* | (v_{I-1} | v_{N-I:N} = v_{I-1})] \tag{4}$$

where $1 \leq I - 1 \leq N$ is the first rejected bidder. Then, the conditional distribution of the expected equilibrium price given that $v_{(I-1:N)} = v_{I-1}$, is the same as the distribution of the (I –1)*th* order statistic in a sample of size I–1 from a population whose distribution is simply $F(v)$ truncated on the right at v_{I+1}. This value changes with I in each auction round and according to the cap. At the same time, one can show that the conditional variance of the valuation of the first rejected bidder, corresponding in expectation to the above closing price is

$$\sigma_{N-I+1:N}^2 = E\left[v_{N-(I+1):N}^2\right] - \mu_{N-I+1:N}^2$$

Over time the variance depends upon $I_t - 1$ and therefore it is not constant from one auction round to the next even if one assumes that $E[v^2]$ and N remains constant over all auction rounds (same number of participants having valuations that do not change from one round to the next). At the same time, one can model the covariance between the equilibrium price and the valuation of the first non-winner as

$$Cov(v_{I:N}, p^* | p^* = v_{I-1}) = \mu_{I,I-1:N} - \mu_{I:N}\mu_{I-1:N}$$

Being the result of a multiunit auction in which bidders may win more than one object, the above results suggest that the equilibrium price dynamics depend upon the number (and the changing identity) of winners –and not only upon the number of participants and their valuations as it is with multiunit singleton auctions. Moreover, it should also be clear that valuations (including the expected value of the highest valuation among non-winners) depends upon the accumulated and unused bank of allowances and their regime as well as the price at which they have being bought. Since the number and the valuations of winners change from one round to the next, time variations in price volatility seems likely. With a time declining cap (see sections 1) the above conditional (on non-winners' past valuations) variance may possibly positively depend on its history and show signs of volatility clustering.

Consequently, one may argue that the variance of equilibrium prices (and returns, too) at a given auction round is proportional to the rate of information arrival as they are convoyed by number of winning bids and other market information such as bid spread and cover ratio. As a result, volatility clustering could be a reflection of the serial correlation of information arrival frequencies. Since all bidders simultaneously receive the new price signals, the shift to a new equilibrium is immediate, and there will be no intermediate (between rounds) partial equilibrium.

3. The data set

This paper covers the third phase EU–ETS (2013-2020). Data generation process has the following main characteristics.

- A single EU-wide cap on emissions replaced the previous system of national caps. It was fixed at 2,084 Million Tons CO_2 in 2013, which was annually reduced by a linear reduction factor (currently 1.74% roughly corresponding to 38.3 million allowances). This amounts to a cap of 1,816 MtCO2e in 2020.
- The MSR was introduced. It functions by triggering adjustments to annual auction volumes in situations where the total number of allowances in circulation is outside a certain predefined range. Allowances may be removed from auction volumes and added to the MSR if the surplus in the market is larger than a predefined threshold, or removed from the MSR and added to current auction volumes if the surplus is lower than a predefined threshold. Additionally, if the allowance price is over three times the average price of allowances during the two preceding years for six consecutive months, 100 million allowances will be released from the reserve. The MSR is intended to address the imbalance between allowance supply, which is currently fixed, and demand, which changes with a number of economic and other drivers
- Auctioning is the default method for allocating allowances (instead of free allocation), and harmonized allocation rules apply to the allowances still given away free.
- More sectors and gases are included
- Auction rules are dictated by Commission Regulation (EU) No 1031/2010 of 12 November 2010.

Accordingly, we consider each (national) auctions as a part a European unitary auction market that takes place in successive periods (working days) in different virtual locations as part of a single allocation mechanism having common design and management. Therefore, the time series of equilibrium prices recorded in each market is regarded as a series of realizations of winning bids presented by bidders operating on the common EEE Exchange platform in the entire European market as a result of a consistent multiunit first price sealed bid strategy.
Data are described in the table below. In order to consider previous trends the data set includes 2012.

Tab. 1 *Data set (December 2012 – March 2020). Working days observations.*

	DEFINITION	OBS.	MEAN	MAX	MIN	S.D.
Price	*Auction Closing Price (Euros/TON-CO_2)*	1,581	10.40	29.46	2.65	7.48
Return	*$Log(Price_t) - Log(Price_{t-1})$*	1,580	.000735	.2388918	-.5296	.040709
Volume	*TON-CO_2 traded (Cap in each auction)*	1,581	3139344	5738500	95000	1117305
Cover Ratio	$\frac{Total\ Bid\ Volume\ of\ Allowances}{Available\ Volume}$	1,554	3.09	13.86	1.12	1.56
Excess	*Recorded Excess demand (TON-CO_2)*	1,554	5972132	2.53e+07	58240	3702019
N	*Number of active Bidders*	1,554	19.76	32	2	4.83
I ≤ N	*Number of successful Bidders (winners)*	1,554	13.96	28	1	4.37
Revenues	*Closing Price × Volume sold*	1,554	3.25e+07	1.29e+08	576000	2.52e+07

Bid Spread	*Max Bid – Min Bid in each auction (Euros/TON-CO2)*	1,554	4.47	31.99	.070	4.77
TAB	*Total amount bid = (bid_i ×$Volume_i$ × N) (An indicator of total willingness to pay at each round)*	1553	9162391	29300000	170000	4074771
AVWB	*Average Volume Won per Bidder (TON-CO_2)*	694	226937	601857	26375	87753.1
SDW	*S.D. of Volumes Won per bidder*	695	288279	835570	0	121828

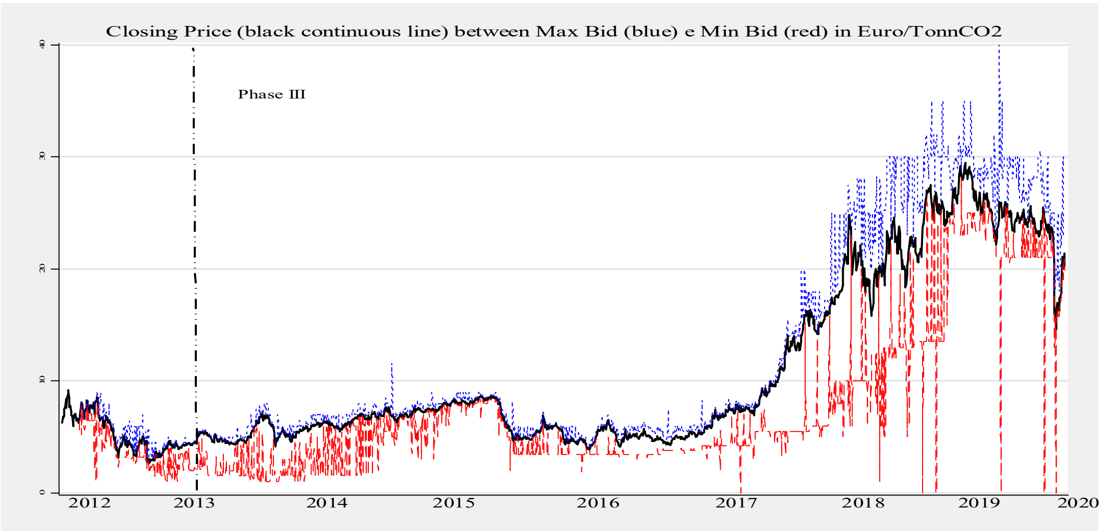
Source: The European Energy Exchange (EEX). https://www.eex.com/en/

The reason for choosing the selected time interval (Phase III plus 2012) is twofold. On the one hand, it is motivated by the desire to avoid the 2008 price drop not specific to the EU ETS. Many other asset values (e.g. stocks, bonds, crude oil, and gas) experienced similar declines and their dynamics may have affected ETS prices. After recovering somewhat in early 2009, the EUA price experienced a 2-year period of stability—with a price around 15 euros—until the summer of 2011, when it fell again by around 50 percent, to a new low of 7–8 euros in 2012, before falling yet again, to around 4 euros as phase III began. During these years, the EUA price has varied considerably, even if the variations were smaller than variations recorded in late 2006 and 2007, when the prices of phase I and phase II allowances also diverged significantly. On the other hand, an examination of the price of EUAs at the end of phases I and II and the size of the allowance surplus accumulated in each phase highlights the importance of banking and its role in establishing a floor on prices. According to (Ellerman et al., 2016, 98) , the surplus was 83 million allowances at the end of phase I and 1.8 billion allowances at the end of phase II (European Commission 2015b), yet the price did not go to zero in 2012 as it did in 2007. This is because the phase I surplus allowances could not be carried over for use in phase II, whereas phase II allowances could be banked for use in phase III and later years when the cap became even lower and prices were expected to be higher. If one take into account that in Phase III a single EU-wide cap on emissions replaced the previous system of national caps (see above), it is clear (Ellerman et al., 2016, 98) that phase I and phase II constituted separate markets with differing degrees of expected scarcity, specific organizational forms and different data generation processes. Hence, I excluded them from the analysis.

4. Prices and Returns

This section starts with the analysis of the main characteristics of the *Price* as a time series. The following plots illustrate the dynamics of *Price* over the entire sample period covered by this study. This figure shows the prices of the next December futures contracts, which have become the main trading instruments in the EU–ETS. At first glance, one may detect a tendency of large changes to follow large changes and small changes to follow small changes, which implies volatility clustering.

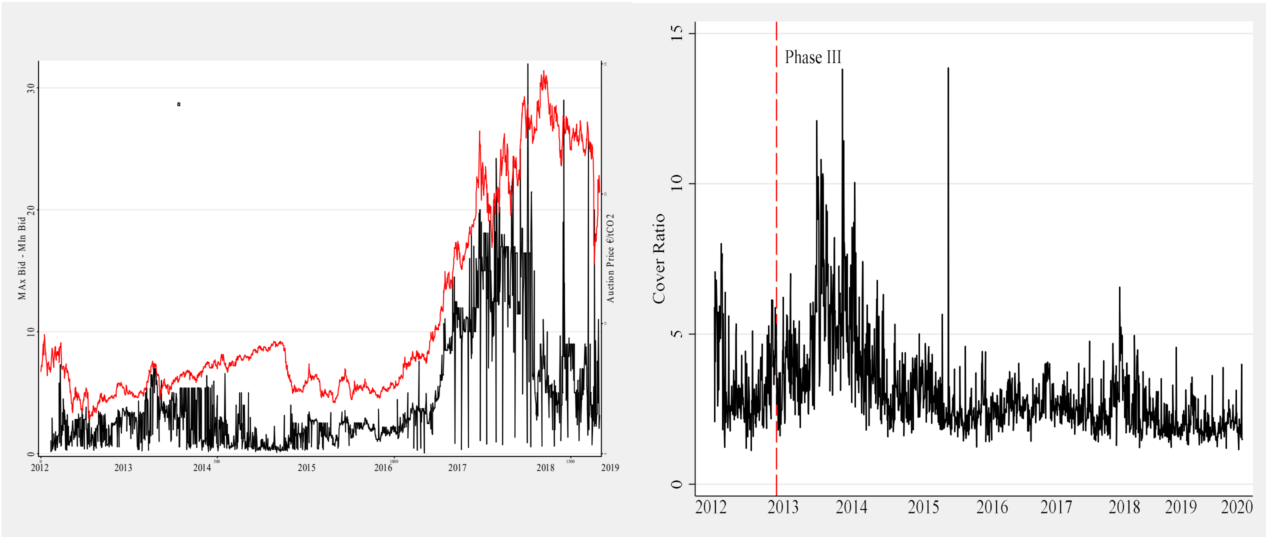
Fig. 1 *Prices 1/2012 –3/ 2020 (Phase III started in 2013) MSR and back-loading were introduced in 2018*



More in details, the plot prompts two comments. Until the second half of 2017, the price is always lower than 10 euros and shows little variations with respect to maximum bids. The level of prices in 2012 was very small (due to general causes, e.g. the protracted effects of the economic crisis of 2008) but still greater than zero in despite that the surplus of allowances accumulated during phase I could not be carried over for use in phase II. On the contrary, phase II allowances could be *banked* for use in phase III and later years when the cap was expected to be even lower and prices are expected to be higher. As for this period, one might hypothesize that full bid disclosure was another reason that encouraged low bidding as bidders sought to hide their true valuations from the other market participants and pooled bids at or below the equilibrium price. Note that as stressed by Benz and Trück (2009, 5), aspects concerning the regulatory framework like explicit trading rules (e.g. intertemporal trading), the linkage of the EU ETS with the market of project-based mechanisms and/or with the Kyoto Market in the future have an important impact on prices, too. From 2017, the closing price increased steadily as well as the bid spreads. Bidding became more aggressive (i.e. higher) and the bid spread shows jumps and spikes as it is made more evident by the following Figure 2. The plot shows a further sharp increase in prices at the beginning of 2018 and this may be related to the introduction of measures affecting the supply side of the market. EU authorities enforced quantity-based interventions, such as back loading[9] and the "Market Stability Reserve" (MSR) in 2018. The latter imposes that if the total number of allowances in circulation was less than 400m in a year, then the MSR releases 100m allowances into circulation in the following year. If it was between 400m and 833m, then no release or absorption had be introduced in the market and, finally, if it was greater than 833m, then the MSR had to reduce the volume of allowances auctioned in the subsequent year by 12 per cent of allowances in circulation. The core impact of the MSR is its governance of the excess quantity in the bank of allowances. This measure reduced the overall supply of allowances by a substantial amount if the bank got 'too large'. This is reflected in the higher values of the *Bid Spread* after 2018 and in the reduction of the *Cover Ratio* (Fig.2).

[9] Back loading changes the scheduled quantities of auctioned allowances so that fewer are auctioned in the early years and more are auctioned in the later years of phase II. After some debate, the decision was made in February 2014 to withdraw 900 million allowances from auctioning in 2014–2016 and to add them back in to auctioning in 2019–2020.

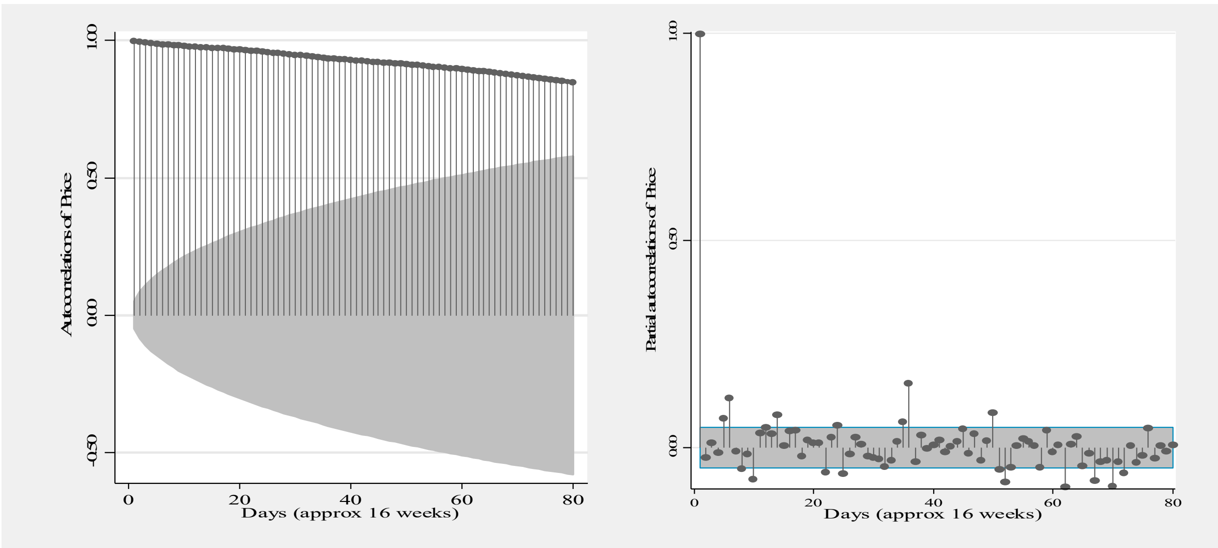
Fig. 2 *Price behavior (upper red line) and Mean Bid Spread across bidders (black line) defined as (Max Bid – Min Bid) (left plot with double scale). Cover Ratio (right plot)*



4.1 *Price* Autocorrelation and *Price* stationarity

I look at the autocorrelation properties of *Price*, which is shown in the following plots of the ACF and PACF.

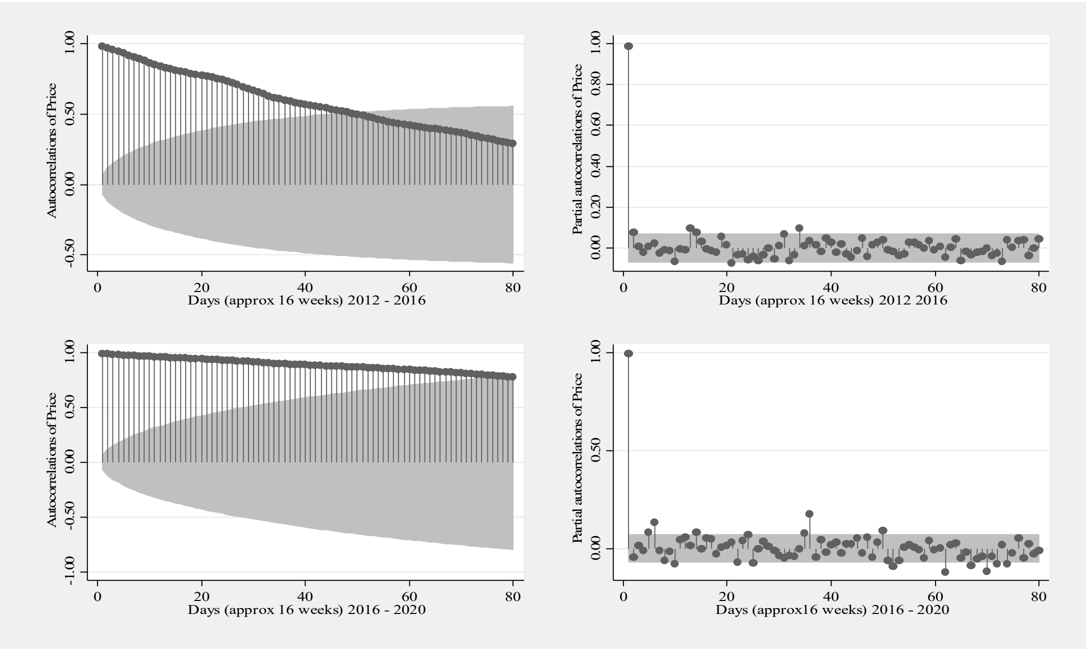
Fig. 3 *AC and PAC of Price over 16 weeks (1/2012 – 3/2020)*



As one can see, the decay of the autocorrelation function is very limited and estimated coefficients are outside the 95% CI for any lag between 0 and 80 auction rounds (approximately four mounts). Then, the ACF coefficients are not zero and *Price* is not a random walk. At the same time, the coefficients of the partial autocorrelation function are very low and rarely significant.

On the contrary, when the analysis is conducted for two sub periods, the results change as it is shown in the plots below.

Fig. 4 *AC and PAC of Price over 16 weeks (2 subsamples: January 2012 – July 2016; august 2016 – February 2020)*



During the first period, (2012 – 2016), the ACF decay is stronger and after the first 4 weeks the autocorrelation is not statistically significant as if the lags behold the first mount after each auction round were losing their relevance. From 2016 to 2020 the ACF coefficients are not significantly different from zero for any lag with the (irrelevant) exception of the last four. The last sub sample is characterized by the introduction of the MSR reform (see above) together with the stricter LRF and possibly reduced a feeble tendency towards long run equilibrium that was present during the previous sub sample. Recall that in February 2014 it was decided to withdraw 900 million allowances from auctioning in 2014–2016 *and to add them back* in to auctioning in 2019–2020.

4.2 ADF and P-P test of *Price* stationarity

Write the price equation as a first-order autoregressive process:

$$(1 - \varphi L)P_t = \varepsilon_t \tag{1}$$

where L is the lag operator. Stationarity requires that the root of the characteristic equation $(1 - \varphi L) = 0$ which is $L = 1/\varphi$ must be greater than unity in absolute value. Thus, stationarity requires $-1 < \varphi < 1$. The null hypothesis is that *Price* contains a unit root (i.e. that $|\varphi)| \geq 1$), and the alternative is that *Price* was generated by a stationary process (i.e. that $|\varphi)| < 1$). Hence if $\varphi = 1$ the implication is that the first-order autoregressive process (1) is nothing else but the random walk process $Price_t = Price_{t-1} + \varepsilon_t$, and so unity of φ implies non- stationarity of the original time series i.e. that *Price* is I(1). In order to conduct ADF test and to replace tau for t test the model can be rewritten in first difference terms as follows:

$$\Delta Price_t = \alpha + \beta t + \delta Price_t + \varepsilon_t \tag{2}$$

with constant and linear trend and the null becomes $\delta = 0$ for non-stationarity if $t_\delta > \tau$. For stationarity δ is the critical parameter both in (1) and (2). Results are shown in the Table below.

Tab. 2 *ADF test of Price*

```
. dfuller Price, trend regress lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =      1579
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.167	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.5086

D.Price	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Price						
L1.	-.005076	.0023428	-2.17	0.030	-.0096714	-.0004807
LD.	.0241932	.025231	0.96	0.338	-.0252967	.073683
_trend	.0000801	.0000384	2.09	0.037	4.75e-06	.0001555
_cons	-.0023828	.0216096	-0.11	0.912	-.0447695	.0400038

The estimated *t* is greater than the D-F *tau* at any critical level and thus the null is not rejected. Therefore, Prices exhibits a unit root or in other words is not a stationary series.

The same model can be reformulated in terms of first difference of the first differences as follows

$$\Delta(\Delta Price)_t = \alpha + \beta t + \delta(\Delta Price_t) + \varepsilon_t \quad (3)$$

Results are reported below.

Tab *3 ADF test of Price in first differences*

```
. dfuller DPrice, trend regress lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =      1578
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-28.068	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0000

D.DPrice	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DPrice						
L1.	-.9904714	.0352881	-28.07	0.000	-1.059688	-.9212548
LD.	.0130996	.0253375	0.52	0.605	-.0365992	.0627984
_trend	.0000143	.0000237	0.60	0.547	-.0000322	.0000609
_cons	-.0028607	.0216492	-0.13	0.895	-.045325	.0396037

In this case, the *t* values are much less than the theoretical critical *tau* at any level. Therefore, the time series of *Price* differenced once is an I(0) stochastic process and Price in levels is non stationary I(1) stochastic process. When Price is differenced twice it does not exhibit a unit root, or in other words is a stationary time series. Summing up, *Price* is a I(1) process as it is shown by the alternative tests reported in Tab. 4.

Tab *4 ADF and Phillips-Perron test of Price stationarity*

```
. dfuller Price, trend regress lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =      1578

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.134            -3.960            -3.410            -3.120
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.5270

------------------------------------------------------------------------------
D.Price      |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Price |
         L1. |  -.0050098   .0023476    -2.13   0.033    -.0096146   -.0004051
         LD. |   .0246933   .0252644     0.98   0.329    -.0248621    .0742488
        L2D. |  -.0108367   .0253311    -0.43   0.669    -.0605231    .0388496
      _trend |   .0000791   .0000385     2.05   0.040     3.55e-06    .0001547
       _cons |  -.0020923   .0216485    -0.10   0.923    -.0445552    .0403707
------------------------------------------------------------------------------

.  pperron Price, lags(2) trend regress

Phillips-Perron test for unit root                 Number of obs   =      1580
                                                   Newey-West lags =         2

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -7.888           -29.500           -21.800           -18.300
 Z(t)             -2.107            -3.960            -3.410            -3.120
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.5420

------------------------------------------------------------------------------
Price        |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Price |
         L1. |   .9951158     .00234   425.26   0.000      .990526    .9997057
      _trend |   .0000767   .0000384     2.00   0.046     1.45e-06     .000152
       _cons |  -.0011023   .0215867    -0.05   0.959    -.0434439    .0412394
------------------------------------------------------------------------------
```

4.3 Price and Return

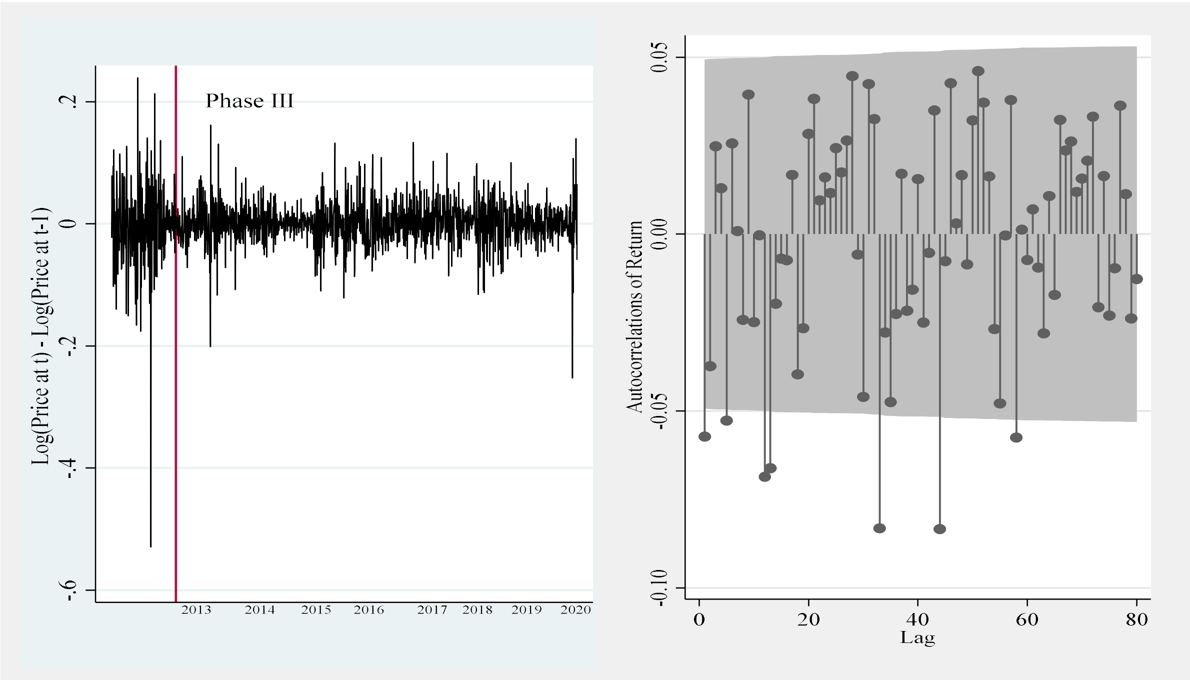
Fig. 5 below shows a plot of the EUA log-returns $R_t = ln(p_t) - ln(p_{t-1})$ and the ACF for the whole sample. As it was found by Benz and Trück (2009, 8) for a period antecedent the one analyzed here (January 3, 2005–December 30, 2005), the data show heteroskedasticity and volatility clustering and both maximum positive and negative log-returns could be observed. It is interesting to compare the *Return* sample summary statistics of Benz and Trück (2009, 8) with those of this paper. The table below makes the comparison and reinforce the arguments summarized when commenting Tab. 1 for excluding phases I and II from the analysis.

Tab 5 *Summary statistics of Return*

	Observations	MEAN	MEDIAN	MIN	MAX	SD	Skew	Kurt
Benz-Trück (2009)	256	0.0037	0.0046	-0.1528	0.1298	0.0319	-0.83	8.57
This paper	1,580	0.000735	0.000	-.5295581	.2388918	0.0408	-1.44	24.5

Return volatility has not changed dramatically over time in spite of a sharp reduction of the mean and median values but the shape of the distribution has. Return exhibits an increased positive skewness and excess kurtosis. Hence, estimations should allow for volatility structure, asymmetry and excess kurtosis should provide a better fit to the time series.

Fig 5 Log-returns: $R_t = ln(p_t) - ln(p_{t-1})$ and *ACF of* R_t



Instead, there is a degree of autocorrelation in the riskiness of returns and clear signs of volatility clustering. As for the former we finally test for ARCH effect after running a simple OLS autoregressive model of price and return. ARCH test are reported below.

Heteroskedasticity Test: ARCH estimate of *Price*

F-statistic	82.78215	Prob. F(1,1577)	0.0000
Obs*R-squared	78.75311	Prob. Chi-Square(1)	0.0000

Heteroskedasticity Test: ARCH estimate of *Return*

F-statistic	3.765888	Prob. F(1,1576)	0.0525
Obs*R-squared	3.761679	Prob. Chi-Square(1)	0.0524

The null of absence of ARCH effect in the *Price* series must be rejected at any level of significance but not for *Return*. Summing up, one can stress that given the objective function of bidders (which includes bank, i.e. accumulated allowances whose value depends on future prices) the accuracy of the predictions of the price model is important. Thus, the key issue is the variance of the error terms, and about what makes them small or large. The question –which is typical of financial applications where the dependent variable is the return on an asset or portfolio and the variance of the return represents the risk level of those returns–, emerges in modelling CO_2

auction prices too. It advocates that errors be handled properly and the variance of the dependent variable should be modeled as a function of past values of the dependent variable and independent, or exogenous, variables. This research strategy is followed in the next section.

5 Alternative GARCH models of equilibrium prices

ARCH processes, being autoregressive, depend on past squared observations and past variances to model for current variance. GARCH aims to minimize errors in forecasting by accounting for errors in prior forecasting and, thereby, enhancing the accuracy of ongoing predictions. The following table summarizes the alternative versions of the empirical model used in this section.

Model	Specification 1	Specification 2	Specification 3
$p_t^* = \alpha + \beta' \boldsymbol{X}_t + u_t$ $u_t \mid \Omega_t \sim iid\ N(0, h_t)$ i.e. Conditional Normal Error	**pure autoregressive** ***X*** includes only a constant and *Price* at *t-1* (no trend)	***X*** includes a constant, *Price at t-1 and other exogenous variables*	***X*** includes a constant, *Price* at *t-1* with or without exogenous regressors Plus exogenous explanatory variables for variance
	Variance Equation		
	$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_\gamma u_{t-j}^2$ (p, q) to be specified	$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_\gamma u_{t-j}^2$ (p, q) to be specified	$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_\gamma u_{t-j}^2 + \sum_{k=1}^{m} \mu_k Y_k$ (p, q) to be specified $\boldsymbol{Y_t \neq p_t}$ exogenous variance regressors

In all specifications, I assume coefficients have to satisfy $\sum_{i=1}^{p} \delta_i + \sum_{j=1}^{q} \gamma_\gamma < 1$; $\delta_i, \gamma_\gamma \geq 0; \gamma_0 > 0$ to ensure stationarity and a strictly positive conditional variance.

Looking at the first column, I stress that no version adopts the variant of including the s.d. or the variance in the mean equation (ARCH-M model, where the estimated coefficient on the expected risk is a measure of the risk-return tradeoff, which would be meaningless in the present case). Neither the hypothesis of Generalized Error distribution is adopted because the estimated coefficient would be of difficult interpretation. The first two versions (second and third columns) are the most widely used GARCH specification and assert that the best predictor of the variance in the next period is a weighted average of the long run average variance, the variance predicted for this period and the new information belonging to this period, which is the most recent squared residual. Such an updating rule is a simple description of adaptive behavior. With version 3, I assume that bidders update the predicted variance using some exogenous regressors (other than the lagged price) representing new information affecting their bidding behavior. Note that the forecasted variances from this model are not guaranteed to be positive. Yet I introduce regressors that are always positive to minimize the possibility that a single, large negative value generates a negative forecasted value. As we shall see, the total number of bidders and the cover ratio (a measure of excess demand) will be important innovations explaining the predicted variance perfectly consistent with the theoretical findings of section 2. Results are reported in the table below.

Tab. 6 Various *GARCH estimates (z-stats in parenthesis)*

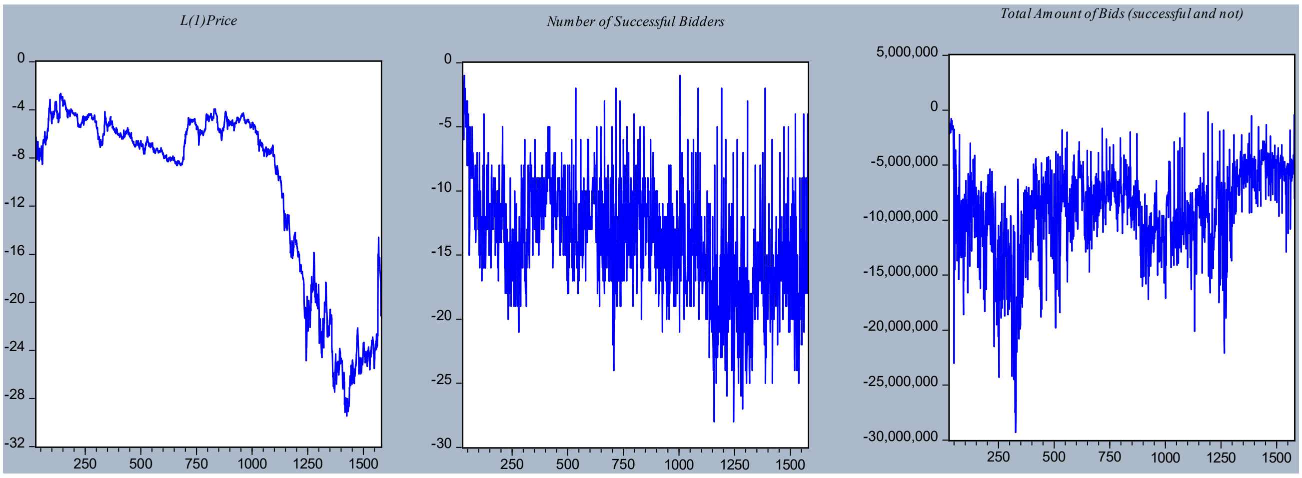
	1	2	3	4	5	6	7	8
MEAN EQUATION of Price								
N after adjustments	1579	1552	1580	1552	1552	1552	1552	1552
C	5.17	8.2	0.02	-0.013	0.062	0.11	0.096	35.6
	(364.5)	(41.8)	(1.52)	(-1.04)	(2.99)	(3.50)	(2.92)	(0.10)
Price (-1)			0.99	0.99	0.99	0.99	0.99	
			(715)	(1105)	(571)	(532)	(642)	
AR(5)		0.97						0-99
		(1136)						(184)
MA(5)		-0.15						-0.46
		(-10.8)						(-9.9)
Bid Spread = Max_bid - Min_bid					0.008	0.009		
					(3.21)	(3.65)		
N. of Winners					-0.004			
					(-2.84)			
N. of Winners/Total Number of Bidders						-0.09	-0.08	
						(-2.72)	(-2.56)	
TAB = Total Amount Bid						-3.53E-09	-1.92E-9	
						(-2.22)	(-1.22)	
VARIANCE EQUATION								
C	0.02	0.01	0.0006	0.097	0.0005	0.000514	0.02	13.8
	(4.34)	(7.7)	(5.05)	(9.67)	(4.75)	(4.82)	(2.21)	(18.53)
Resid(-1)^2	0.64	0.7	0.09	0.34	0.085	0.084118	0.11	1.14
	(7.02)	(13.5)	(14.3)	16.26	(16.20)	(16.33)	(12.4)	(4.11)
GARCH(-1)	0.36	0.42	0.91	0.35	0.92	0.92	0.86	-0.085
	(8.37)	(18)	(15.5)	-24.42	(20.6)	(21.2)	(78.9)	(-5.72)
N Bidders				-0.003			-7.38E-05	-0.47

				(-5.35)			(-1.7)	(-15.9)
Bid Spread				0.004			0.009	0.23
				-6.85			(7.3)	(9.97)
Cover Ratio				-0.005			-0005	-0.35
				(-17.8)			(-3.5)	(-14.47)
HETEROSCEDASTICITY ARCH LM TEST								
F-stat	2.02	13.14	5.28	0.45	5.30	5.45	0.25	22.56
(Prob.)F	0.16	0.0003	0.021	0.5	0.02	0.02	0.62	0.0000
N×R^2	2.02	13.05	5.27	0.45	5.29	5.44	0.25	22.26
(Prob.)χ^2 See the above *N* for DF	0.15	0.0003	0.022	0.5	0.02	0.02	0.62	0.0000

The circle indicates that the null of absence of ARCH effect must be rejected at any level of significance. This implies that versions based on estimations of the mean equations in which there are no exogenous regressors perform poorly with respect to alternative versions. The inclusion of (weekly) AR and MA corrections does not improve results even when the variance equation includes regressors (version 8). This finding accords with previous empirical results (Benz and Trück 2009, 11). Before commenting the above result, I stress that I reiterated the process with higher orders of ARCH processes and/or GARCH processes of different distributions (GED, student-T etc.) but that the above reported structure (Tab. 6) produced standardized residuals that are the closest to white noise. Note that in all specifications the highly significant positive coefficient of GARCH(-1) implies persistent volatility clustering. Version (8) produces implausible GARCH results.

Results show that the number of successful bidders as well as the total monetary amount bid affect negatively, as expected on the basis of results obtained in section 2, the equilibrium price whereas the total number of bidders (winners and non-winners) and the cover ratio (interpretable as a measure of auction inefficiency) reduce volatility. On the contrary, the bid spread (the difference between maximum and minimum bid in each auction round) increases it. Total number of bidders and minimum bid always increase volatility. The number of successful bidders as well as the total amount bid affect negatively, as expected on the basis of results obtained in section 3, the equilibrium price whereas the total number of bidders and the cover ratio (a measure of auction inefficiency) reduce volatility whilst the bid spread increases it. Yet, the effect of the variation of $L(1)p^*$ on current p^* changes appreciably over time as it is show in the following plot where numerical derivatives are shown. The plot shows the numerical value of the derivatives of each regressors of the mean equation based on the estimated regression. The autoregressive effect of the lagged price is stable from Phase II to past the mid of Phase III and then drops at the beginning of 2019 to increase sharply again between 2019 and 2020. On the contrary, the number of successful bidders and the total amount bid (by all bidders) always affect negatively the equilibrium price but the values of the derivatives do not show a specific time path.

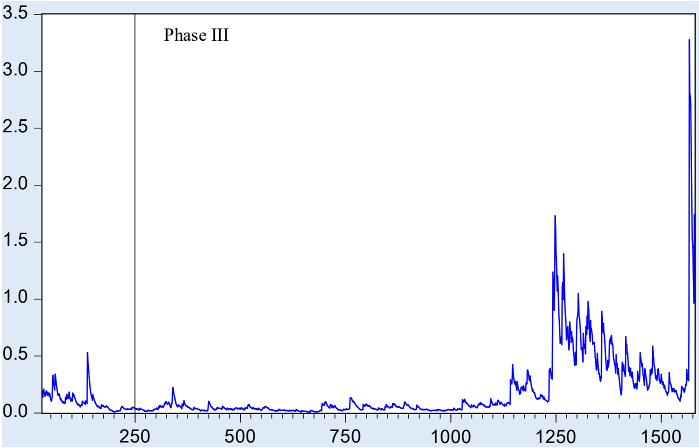
Fig. 6 *Round-specific derivatives of the estimated mean coefficients*



One may note that the impact on current price of the lagged price is stable until approximately the end 2016 to increase sharply in absolute value since the beginning of 2017. This implies that during the first part of Phase III a price stability prevailed and some observers could interpret this fact as the effect of the prolongation of the economic crisis that strongly affected industrial output and induced a "surplus" of allowances (de Perthuis and Trotignon, 2014). Yet, as the same authors note with respect to a partially different time period, this rationale is incomplete and does not allow to draw the correct lessons from the functioning of the market and thus to propose adequate recommendations.
Estimations also lead to some reflections concerning the estimated conditional variance. In the following plot, the time path of estimated conditional variance mirrors the first panel of Fig. 6 above where the marginal effect of *L(1)Price* had a flipped *S* shape with an increased absolute value of the derivative for observations recorded towards the end of Phase III. Recall, moreover, that in all estimations of the variance equation the sum of the ARCH and GARCH coefficients was very close to one in all specifications of the model. This implies that in the data generation process shocks affecting the conditional variance are highly persistent. This is quite evident for the last part of the Phase III period when innovations in the auction rules were introduced (see section 2 for a discussion). The plot (Fig. 7) shows the increased volatility from the end of 2017 to 2020 as it emerged from a model where the variance equation was predicted after controlling for some exogenous regressors (version 7). Still, even after controlling for those factors the volatility shows a sharp increase due to the above innovations[10]. Indeed, when

Fig. 7 *Estimated conditional variance (GARCH version 7)*

[10] Plots obtained from different multivariate version of the GARCH model are similar.

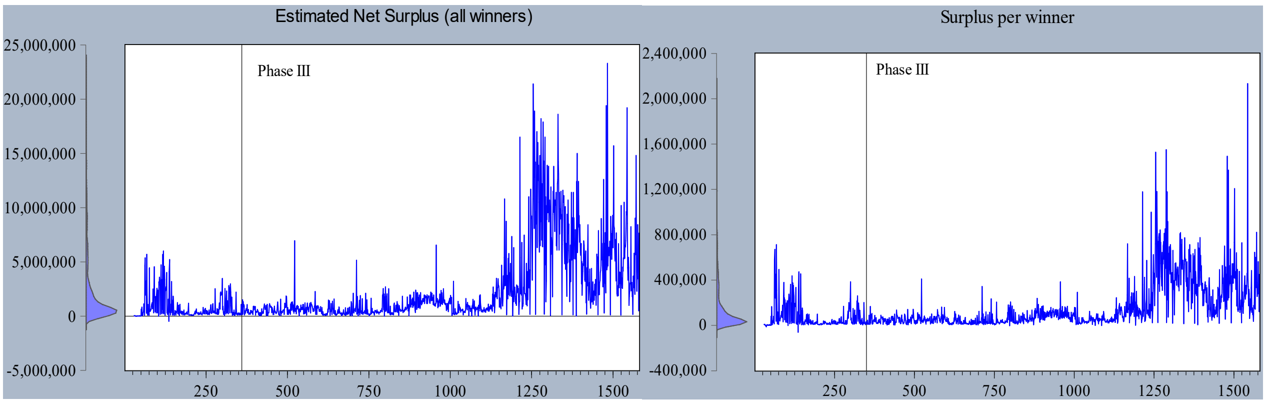


interpreting the above plot one should recall that in addition to the introduction of the already discussed linear reduction factor and the MRS adjustment scheme, in Phase III a single EU-wide cap on emissions replaced the previous system of national caps thereby aggregating isolated national allowance markets into a single European market. The number of participants increased (new entrants and small traders) as well as market liquidity. Hence, a dynamic consequence of the auction reforms introduced in the second half of Phase III and of the accelerated reduction of the total cap from one year to the next is that this new environment increased the volatility of the equilibrium prices as it was shown in section 3. An increased volatility of prices during the last two years of Phase III generated a large amount of volatility in that and subsequent period.
Finally, the above estimates can be used to evaluate the surplus winners realize in each auction. A rough measure of surplus is simply $S_t = 0.5(MaxBid_t - \widehat{p_t^*})Volume_t$ where the hat refers to the predicted values of the equilibrium price. The series generated according to this formula is shown in the following plot. Recall that from Definition 3 of section 2 we have

$$p^* = E[b(v_I, Q_I)|v_{I:N} > v_{I-1\in N}] = E[v_{I-1:N}|v_{I:N} = V]$$

Hence, we interpret the *predicted* price as an approximation to the *predicted* expected value of allowance valuation of the first excluded bidder. The first panel shows the series of the aggregated surplus of winners and the second the average surplus defined as S_t/I_t.

Fig. xx *Estimated Net Surplus and per capita Net Surplus in euros (kernel densities on the vertical axis)*



8. Conclusions

Linking a model of bidding behavior and the GARCH analysis of auction equilibrium prices is the main contribution of this paper. Equilibrium in EU-ETS auctions implies that the expected mean and the conditional variance of marginal (equilibrium) bid depend on the valuation of the allowances (i.e. the costs of pollution reduction activity) of the first non-winning bidder in each auction and on the number of winning bids. Given auction rules and optimal bidding behavior, empirical prediction of equilibrium price series cannot rely on constant variance methods. Estimations run with GARCH methods indicates that although a cap-and-trade system like EU ETS is possibly helpful in guaranteeing a credible and binding reduction of emissions within the ETS sectors yet the increased volatility recorded during the last part of Phase III and the parallel increase in bidders surplus are at odds with efficiency. The latter result accords with the finding that Bid Spread increases volatility whereas the number of bidders reduces it. The gradual yearly reduction of allowances will probably be a key factor to obtain a long run deep reduction of carbonization within EU ETS but measures to stabilize equilibrium prices (e.g. price max and min levels) could help to improve efficiency. EU has expressed further pollution reduction ambitions with European Green Deal –to be implemented by further reductions of the LRF. Yet reliance on just market mechanisms, such as a greatly volatile EU-ETS, might prove insufficient.

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