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EU ETS Spot Volume Modeling and Forecasting

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Abstract

The aim of this project is to model and predict the daily trading volumes of carbon emission allowances in the context of EU ETS (European Union Emission Trading System). The analysis is performed by considering different autoregressive models, eventually with ARCH/GARCH structure since there is evidence of volatility clustering. After selecting the model with the best information criteria, we use it to predict out-of-sample data obtaining an error of 3% in terms of magnitude of the volumes with respect to the real data. Finally, we find that adding the prices of coal as exogenous variable, is statistically significant for EU ETS volume prediction.

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1 Introduction and Literature Review

1.1 Introduction

The European Union Emissions Trading System (EU ETS) is a milestone of the EU's policy to combat climate change and a crucial tool for reducing greenhouse gas emissions in a cost-effective manner. Launched in 2005, the EU ETS was the world's first and still remains the largest carbon market, covering more than 11,000 power stations and industrial plants in 30 countries, as well as airlines operating between these countries. The system operates on a "cap and trade" principle, where a cap is set on the total amount of certain greenhouse gases that can be emitted by installations covered by the system. This cap is reduced over time to decrease total emissions. Within the cap, companies receive or purchase emission allowances, which they can trade with one another as needed. This creates a financial incentive for companies to reduce their emissions: those that can cut emissions cheaply can sell their excess allowances to those facing higher costs. By putting a price on carbon, the EU ETS encourages businesses to invest in cleaner technologies and more efficient processes, thereby driving innovation and reducing overall emissions.

The system has undergone four main phases of reform to improve its effectiveness, including measures to address the surplus of allowances and to strengthen the market stability reserve. As part of the European Green Deal, the EU ETS is being expanded and strengthened to ensure the EU meets its ambitious target of reducing net greenhouse gas emissions by at least 55% by 2030 and achieving climate neutrality by 2050.

Most existing literature on this topic aims at predicting prices and volatility instead we focus on trading volumes.In particular, the third phase of the EU ETS (from 2013 to 2020) is the one in which the market has reached a higher maturity, so we decided to focus the analysis on this period. Moreover, we thought that the inclusion of some exogenous variables would have improved the results of the prediction on out-of-sample data. In particular we used the following ones: Brent oil daily price, coal price, future prices and VIX.

1.2 Literature Review

The first research on the ETS, carried out around and just after its launch in 2005 focused on finding determinants for the EUA price. Christiansen et al. ([1]) identified three key drivers for the market price in the ETS: policy and regulatory issues, market fundamentals and technical indicators. Following this, Mansanet-Bataller et al. ([2]) were the first to investigate econometrically the relationships between energy markets and the EUA price. They found that the most emission intensive energy variables, i.e. coal, Brent oil and natural gas, are the most important ones in the determination of EUA returns.

Concerning the class of models that we have chosen to use, Paolella and Taschini ([3]) used an AR(1)-GARCH(1,1) model to capture heteroskedasticity in the EUA returns. Finally, Ljungqvist and Palmqvist ([4]) used several ARMA-GARCH models, including exogenous inputs like electricity, coal, Brent oil and gas prices, to model return and volatility of the most traded EUA futures contracts.

2 Data and Methodology

2.1 Data

The main data we worked with is the time series of all the traded volumes in the EU-ETS market. In particular we have taken into consideration data between the 01-01-2013 and the 05-05-2020, since this dates correspond the third phase of EU ETS system, the more mature and concluded one.Specifically the in-sample dataset runs from 01-01-2013 to 12-09-2019 and we have an out-of-sample period of 13-03-2019 to 05-05-2020. The descriptive statistics of this data are shown in the following table:

Dataset	Size	Mean	Min	Max	Std. Dev.	Skew.	Kurt.
In-sample	1937	7.8e+07	1.0e+00	2.2e+10	5.2e+08	3.7e+01	1.5e+03
Out-of-sample	293	5.1e+07	1.0e+00	2.3e+09	1.5e+06	1.2e+01	1.8e+02

Table 1: Summary statistics for the EU ETS traded volume. *Std. Dev.* refers to standard deviation, *Skew.* to the skewness, and *Kurt.* to the kurtosis.

Some data-cleaning has also been made: we have eliminated all observations corresponding to weekend days since the volume was usually considerably lower and not reliable. We have also removed observation of the following dates because they represent outliers:

- 1 April 2013: European Parliament rejects the proposal to backload carbon allowances.
- 17 July 2013: European Commission adopts the decision to backload 900 million allowances to stabilize the market.
- 14 January 2015: EU carbon price spikes due to speculation about the ENVI committee vote on the MSR.
- 25 May 2015: European Parliament and Council reach a formal agreement on the MSR.
- 7 June 2018: European Parliament adopts new rules to reform and strengthen the EU ETS, including enhancements to the MSR and the introduction of the Innovation Fund and Modernization Fund.
- 30 May 2019: European Parliament and the Council reach a provisional agreement on the reform of the EU ETS to include the aviation sector more comprehensively.
- 1 April 2013, 17 July 2013: in these days the European Parliament operates on the number of allowances to stabilize the market.
- 25 December 2013, 26 December 2013, 1 January 2014, 26 December 2014, 1 January 2016, 26 December 2016, 25 December 2017, 25 December 2018, 25 December 2019, 1 January 2020: these dates correspond to Christmas and New Year's Eve.

Here we can see a plot of the whole time series:

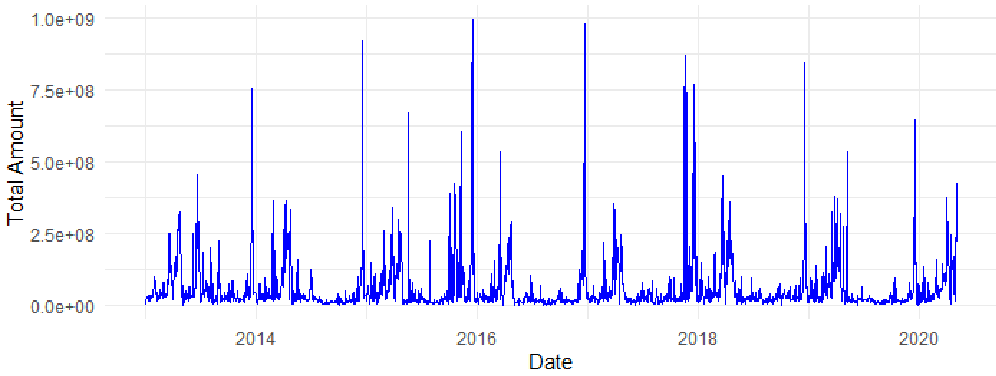

Figure 1: EU ETS daily transaction volume without outliers

2.2 Methodology

In the following sections we explain the methodology we adopted in order to model our problem. Before fitting our models it's important to make sure that the time series we are working with are stationary, if not, to consider some invertible transformation in order to achieve stationarity and still retain the possibility to go back to the original values.We also need to make sure that the models satisfy the usual assumptions on the residuals .We fit different types of ARMA and GARCH models to the time serie and compare their performances on the basis of the BIC information criteria, in order to choose the optimal one

Then we added the exogenous variables to the mean equation of our best model and we used it to perform a forecasting analysis on the traded volumes and their volatility. In the ARMAX model specification, we always consider one lag for the exogenous variables.

2.2.1 Stationarity and Arch Effect Testing

As a first step, we applied a logarithmic transformation to the time series to reduce the magnitude of our data. From the ADF and KPSS tests performed on this time series we observe that the series is not stationary. The results are shown in the first column of the table below. In order to solve this problem we try to differentiate the series. Moreover we apply an arctan transformation: this will be useful later on to avoid fat tails behaviour in the residuals and will allow us to satisfy the gaussianity assumption in our model.

Here are the results for the test, recalling that the critical values for ADF test are -2.58 (1%), -1.95 (5%), -1.62 (10%):

Results of the test	Logartmic time series	Final Time series
KPSS	0.2263	0.0279
ADF	-0.933	-60.56

Table 2: Results of the ADF and KPSS tests before and after the transformations

So our final transformed time series is stationary.

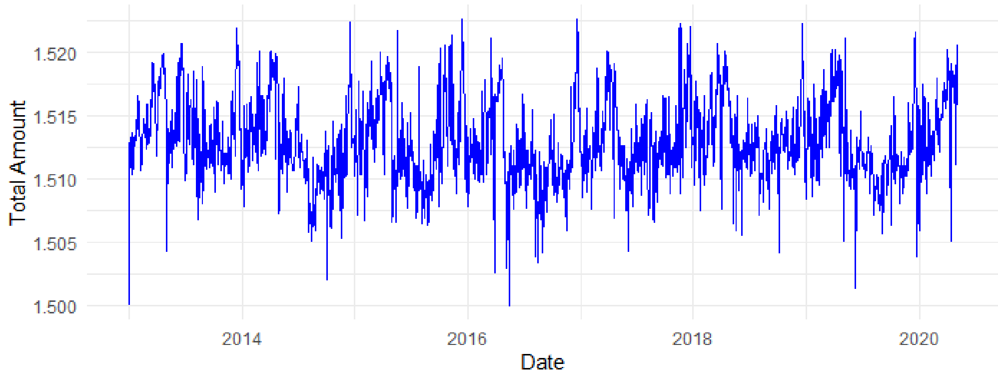

Figure 2: EU ETS daily transaction volume transformed without outliers

Another aspect that we considered is the possible presence of volatility clustering in the time series. We then use a Lagrange multiplier test for the presence ARCH effect in our time series: if the null hypothesis is rejected we can assume that there are ARCH effects present. In our case we observe a statistical test of 39.146 and a p-value of 9.957 so that we can confidently assume the presence of ARCH effect in our time series

2.2.2 Model order choice

In this section we report the steps that led us to the choice of the number of lags for the autoregressive and moving average part of the models that will follow: for this we mainly used the ACF (Autocorrelation Function) and the PACF (Partial Autocorrelation Function) functions that we see below.

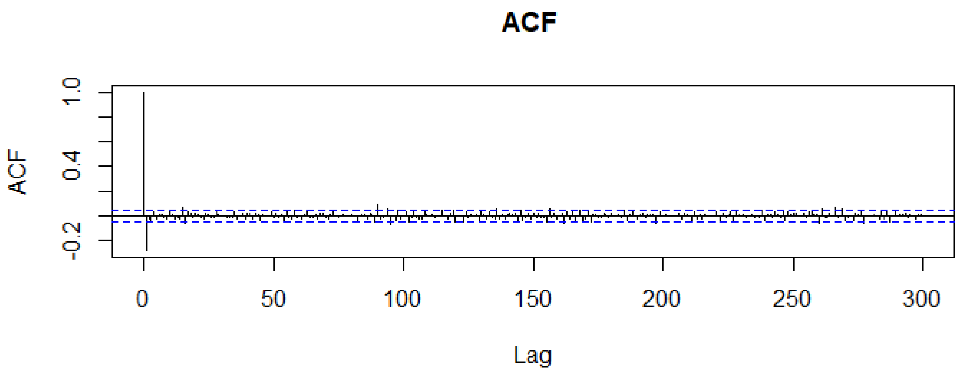

Figure 3: ACF

Regarding the ACF we can clearly observe two distinct spikes followed by a series of smaller spikes which fall inside the confidence interval: we can consider a maximum MA order of 1.

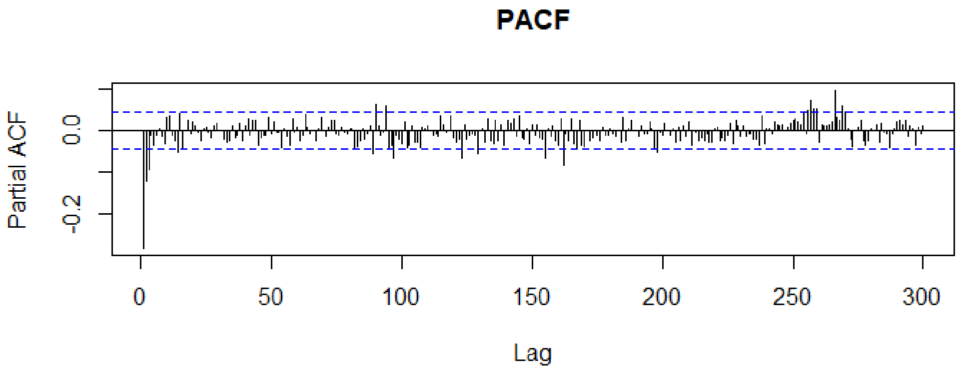

Figure 4: PACF

Similarly by considering the spikes of the PACF function we can consider a maximum AR model order of 3.

2.2.3 Residuals

In order to check that all the assumptions on the residuals are satisfied we will perform Jarque-Bera test and a Ljung-Box test. This will be done to all the models we will fit during our optimal model search.

3 Results

3.1 Modeling

Now we can compare the models in order to choose the optimal one. As previously mentioned, our performance parameter is the Bayesian Information Criteria (BIC). In the following table we report Likelihood and BIC corresponding to each model as well as the number of estimated parameters: the lowest BIC is achieved by the ARMA(1,1)-GARCH(1,1).

As previously mentioned we have verified that all these models satisfy the gaussianity assumptions on the residuals: we report the results just for the optimal model. We obtain for the Jarque-Bera test a p-value of 0.60, while for the Ljung-Box test a p-value of 0.34, so that all the assumptions are satisfied.

Model	k	$\hat{L}$	BIC
AR(0)	3	-1653.0	1.7743
AR(1)	4	-1547.3	1.6656
AR(2)	5	-1509.8	1.6296
AR(3)	6	-1498.9	1.6221
MA(1)	4	-1500.7	1.6159
ARMA(1,1)	5	-1494.4	1.6132
ARMA(2,1)	6	-1494.3	1.6172
ARMA(3,1)	7	-1492.1	1.6189
GARCH(1,1)	5	-1607.0	1.7332
AR(1)-GARCH(1,1)	6	-1511.8	1.6359
AR(2)-GARCH(1,1)	7	-1470.0	1.5953
MA(1)-GARCH(1,1)	7	-1461.30	1.5820
ARMA(1,1)-GARCH(1,1)	7	-1454.1	1.5783
ARMA(2,1)-GARCH(1,1)	8	-1453.5	1.5817
ARMA(3,1)-GARCH(1,1)	9	-1450.6	1.5826

Table 3: Comparison of different models with their parameters, log-likelihood, and BIC values

3.2 Exogenous variables

As previously mentioned, we want to test weather some commonly used exogenous terms may help improve our model performance. In particular we limited ourselves to consider these influencing factors:

- **Brent oil daily price differences**: The price of Brent oil, a benchmark for crude oil, is a key indicator of global energy costs. An increase in oil prices raises the cost of energy produced from fossil fuels, leading to higher interest in renewable energy sources. This drives up the demand for carbon allowances to offset emissions.
- **EU ETS future daily price differences**: We use this as a proxy for the spot price of the transaction.
- **Coal daily price differences**: Since coal combustion is highly polluting, lower coal prices can lead to increased coal use and higher emissions, thereby raising the demand for allowances to compensate for these emissions.
- **VIX daily differences**: A higher VIX indicates greater market uncertainty and risk. During periods of high volatility, market participants may seek to mitigate risks associated with carbon allowance price changes, increasing trading volumes for hedging purposes.

We decided to use in all cases the differenciated time series in order to be coherent as well as to work with stationary data.

In the following table we summarize the coefficients and their significance in different models that we constructed.

	A	**B**	**C**
μ	0.00797	0.00715	0.00748
	(1.5115)	(1.5273)	(1.5918)
ϕ_1	0.1878***	0.18784***	0.18772***
	(3.8754)	(4.1207)	(4.1086)
θ_1	-0.62732***	-0.63334***	-0.63277***
	(-16.7109)	(-19.7662)	(-19.5837)
α_0	0.03508***	0.0341**	0.03392**
	(2.8485)	(2.4525)	(2.4725)
α_1	0.12911***	0.12696***	0.12854***
	(4.7835)	(4.5189)	(4.5959)
β_1	0.75122***	0.7561***	0.75568***
	(12.2784)	(10.9682)	(11.0859)
γ_1		-0.00515	
		(-0.2094)	
γ_2		-0.00556	
		(-0.5802)	
γ_3		0.00388	
		(0.7524)	
γ_4		1.13573*	1.18295*
		(1.6942)	(1.7538)

A = ARMA(1,1)-GARCH(1,1)
B = ARMAX(1,1,4)-GARCH(1,1)
C = ARMAX(1,1,1)-GARCH(1,1)
γ_1=future daily price differences - γ_2=Brent oil daily price differences - γ_3=VIX daily differences - γ_4=coal daily price differences

Looking at the table we can see that the exogenous variables considered don't seem to be very promising since none of them is highly significant in any of the models listed above. The only variable that seems to be significant is the coal price that we will use to perform out-of-sample test.

3.3 Forecasting

As a final test for our model we try to perform a one step ahead forecasting on out-of-sample data using the ARMAX(1,1,1)-GARCH(1,1) model (including coal price differences as an exogenous variable). The test set contains data between 13-03-2019 and 04-05-2020.
Here is the plot of the predicted volumes against the real ones, in which we have also traced the lower and upper bounds of the 90% confidence interval.

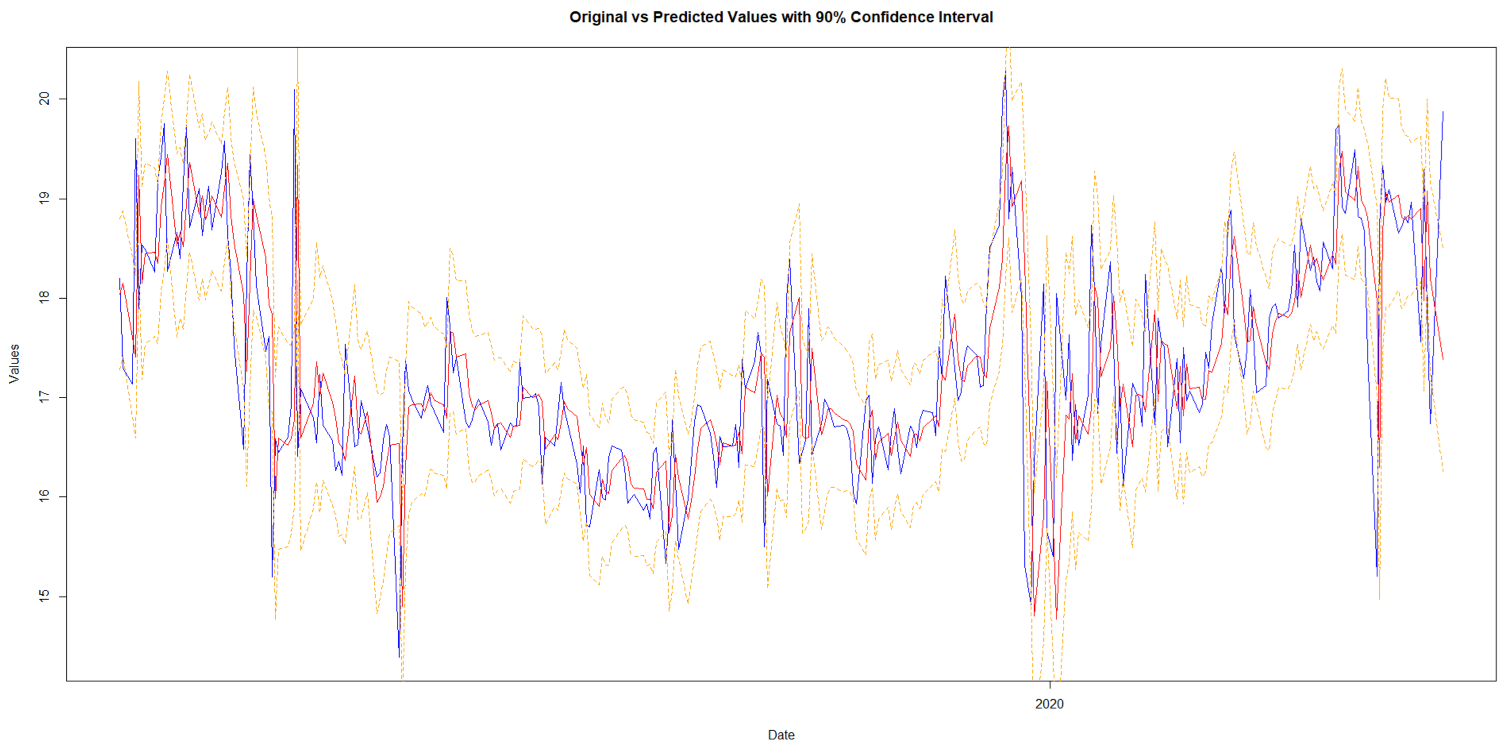

Figure 5: Real data and predicted data with their 90% confidence interval

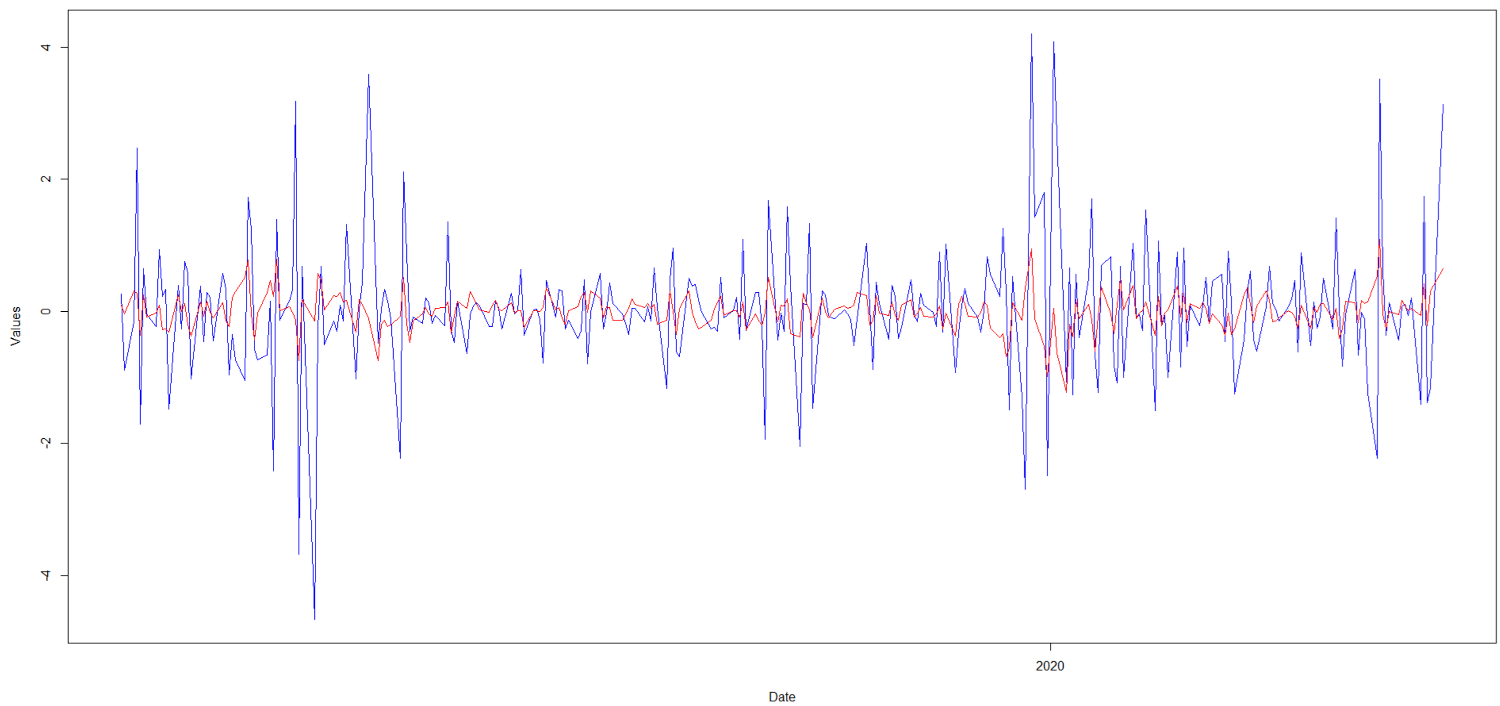

Figure 6: Real data and predicted daily differences

Here are some useful metrics that give an idea of the goodness of the prediction performance

Set	**MAPE**	**Pct**	**MAE**	**MSE**
Volume	77.72%	63.17%	34509452	5.539e+15
Log Volume	3.08%	63.17%	0.534	0.635

Table 4: Performance metrics for the volume time series and the log-volume time series

The model doesn't seem to be performing exceptionally well, even though we clearly have some significance since we manage to predict the sign of the time series correctly around two thirds of the times.

Obviously we observe a great MAPE increase from the logarithmic time series to the original time series of volumes: this is to be expected especially since most of our prediction error comes from periods of real high activity in the market which drastically affect our performance.

Graphically observing the predicted time series, it seems that our model doesn't manage to increase its volatility enough to correctly track the time series during high volatility periods.

Also there are clearly some anomalous events that impact negatively in our prediction, for example we see a great increase in the volatility of our time series at the beginning of 2020 which our model doesn't seem to be managing correctly.

Overall the inclusion of the coal price as exogenous variable doesn't seem to be sufficient to get good results.

4 Conclusions

In this project we consider several models to analyse the traded volumes of the EU ETS contracts. We find that the logarithmic differences of the series is stationary. Moreover we apply an arc-tangent transformation to the data for modelling purposes.

We notice the presence of conditional heteroschedasticity in the residuals, like in previous research, and we introduce a GARCH model to capture the volatility clustering, again in line with existing literature. We consider different AR, MA, ARMA, GARCH and various combination of them. We finally choose the best model using BIC as performance index and we obtain an ARMA(1,1)-GARCH(1,1).

We allow for exogenous inputs in the mean equation of our model but we find that almost none of them is statistically significant. The only one having a little more statistical significance are the coal price differences, so we will include them in our final model.

Finally, we test our ARMAX(1,1,1)-GARCH(1,1) model with a one step ahead prediction and we obtain that we are able to predict almost two thirds of the correct sign changes in the test set of the time series.
In conclusion, although the same parametric model class used in previous literature to predict EU ETS prices seems to work for volumes, the same cannot be said for the exogenous variables, which don't seem to be highly significant in our case.
Obviously further studies could be done to test the significance of different influencing factors.
On the other hand it's possible that, since the EU ETS market is still very sensitive to the continuous reforms and new regulations of the EU ETS system, finding consistently significant exogenous factors may be challenging and this represents a limit to our predictive capability.

5 Bibliography

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