Quantitative Analysis of Carbon Prices

5Â Â Â Â Â Â Â Â Quantitative analysis

The Objective of the following quantitative analysis is to find out if there is causal relationship between the price of EUAs and different fuels and weather data. In the following the time series will be tested for stationarity and then there will be pair wise testing of each of the factors with the EUAs in a bilateral Granger Causality Test.

5.1Â Â Â Â Â Hypothesis setting

Section 4.2 lists fuel and weather combined in the E-t-C as the main price drivers for EUAs.

In the following test I am trying to prove that Oil prices, Gas prices, Coal prices as well as temperature and precipitation influence the price of EUAs.

Â

5.2Â Â Â Â Â Methodology

The first step will be to transform the series to 1st differences of logarithms in order to linearize and stabilize the series.

Â

5.2.1Â Â Â Â Â Â Â Unit Root Test

The Augmented Dickey Fuller Test and the Phillips-Perron test will be performed to test if the series is stationary at a 5% significance level.

Â

5.2.1.1Â Â Â Â Â Â Dickey Fuller Test

Empirical work based on time series data assumes an underlying stationary time series. Therefore we will have to test for that before we conduct other analysis.Â â€œA stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between two time periods depends only on the distance gap or lag between the two time periods and not the actual time at which the covariance is computed.â€[60]

A non-stationary time series will therefore have a time-varying mean or a time-varying variance or both. A common sample for non-stationary is random walk. ()

The stationarity is needed because we want to make general statements, but with a non-stationary series the behaviour can only be studied for the period of time under consideration.

To test for Unit Root the Augmented Dickey Fuller Test (ADF) will be used.

Dickey and Fuller (1981) augmented their regression equation and obtained the augmented Dickey-Fuller test by adding lagged variables to their equation.[61]

Â

Â

The Null Hypothesis will be that there is no Unit Root in the series (Series is stationary). When the value of the T-statistic is greater than the critical value, the H_0 cannot be rejected and unit root is present.

Â

5.2.1.2Â Â Â Â Â Â Phillips Perron Test

Phillips and Perron (1988) proposed an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. It estimates the non-augmented DF test and modifies the ratio of the coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic.

Â

Where is the estimate, and the -ratio of , is coefficient standard error, and is the standard error of the test regression. In addition, is a consistent estimate of the error variance (calculated as , where is the number of regressors). The remaining term, , is an estimator of the residual spectrum at frequency zero.

The PP test will be performed including a constant in the test regression. As method for estimating the default setting â€œBartlett Kernelâ€ will be used.

The asymptotic distribution of the PP modified -ratio is the same as that of the ADF statistic. The results will be checked against the MacKinnon lower tail critical and p-values for this test.[62]

Â

5.2.1.3Â Â Â Â Â Â Akaike Information Criterion

The Akaike is computed in Eviews as:

Â

where l is the log likelihood.

The AIC is often used in model selection for non-nested alternatives. The smaller values of the AIC the better the model. For example, you can choose the length of a lag distribution by choosing the specification with the lowest value of the AIC.[63]

Â

5.2.1.4Â Â Â Â Â Â Schwarz Information Criterion

The Schwarz Information Criterion (SIC) will be used in the Augmented Dickey Fuller Test and the Phillips Perron Test in order to determine the optimal number of lags included in the test regressions. The SIC imposes a penalty for adding regressors to the model.Â Compared to the Akaike criterion it imposes a harsher penalty. The formula is as follows:

Â

Where () is the penalty factor. A lower value of SIC indicates a better model.

Â

5.2.2Â Â Â Â Â Â Â Granger Causality Test

The Granger Causality Test will then be performed on the stationary series.

In theory the Existence of a relationship, found through regression analysis, does not necessarily prove causality or the direction of influence. The basic idea behind the granger test is that only events in the past can cause events happen today and not vice versa.

It is assumed that all the information about the causality is contained in the time series data for the two variables. [64]

The following shows the pair of regressions, which will be estimated while checking for bilateral causality between the price of EUAs and the Oil price.

Â

Â

The first equation postulates that the current EUA price is related to past values of itself and the oil price. The second equation postulates that the current Oil price is related to past values of itself and the EUA price.

Â

Â

Â

Â	Estimated coefficients on the lagged Oil are statistically different from zero (sum alpha does not equal zero)	Estimated coefficients on the lagged Oil are not statistically different from zero (sum alpha does not equal zero)
Estimated lagged oil coefficients are statistically different from zero	Feedback, or bilateral causality	Unidirectional causality from EUA to Oil
Estimated lagged oil coefficients are not statistically different from zero	Unidirectional causality from Oil to EUA	Independence

Table 5â€‘1: Result matrix for Granger Test

Â

Notes to the Granger Causality Test

1. The two variables under observation are stationary
2. Direction of causality may depend critically on the number of included lags. Akaike or Schwarz

criterion can be used to determine the optimal number of lags
3. The error terms are uncorrelated. If that is not true, transformation has to be done.
4. Main focus for causality will be on the results of the F-tests

Â

The subsequent steps will be executed during the Granger Test

1. Obtain the Residual Sum of Squares (RSS_r) by regressing the EUA on all lagged EUA terms (and other variables) without including the lagged Oil variables. (Restricted regressions)
2. Exercise an unrestricted regression by including the lagged Oil terms. Find the unrestricted residual sum of squares ($RSSu_r$)
3. The null hypothesis is , this means the lagged Oil terms do not belong to the regression.
4. This is the test statistic to conduct the F test In the current example m equals the number of lagged Oil terms and k is the number of parameters estimated in the unrestricted regression.
5. The null hypothesis is rejected, if the computed F value exceeds the critical value at the chosen level of significance. In this case the lagged Oil terms would belong to the regression and therefore a movement in Oil causes a movement in EUAs.
6. The same steps will be repeated for the second equation where Oil is the dependent variable. This will show whether EUAs have an influence on the Oil price.

Â

5.3Â Â Â Â Â Data

The EEX started on 09/03/2005 to quote daily prices for EUAs and the available data on weather end on 31/07/2006, therefore in the following data analysis a sample period 09/03/2005-31/07/2006 will be used for the analysis.

Â

EEX Emissions Price

The logarithmic return series of daily price quotations (spot) for EUAs on the European Energy Exchange will be the dependent variable. A monthly time series has been generated using Eviews â€œsum observation methodâ€ and will be analysed together with the coal prices.

Time Series	**Description**
EEXEUAS_LR	EEX price for EUAs, daily, as 1st differences logarithms
EEXEUAS_LRM	EEX price for EUAs, monthly, as 1st differences logarithms

Table 5â€‘2: Time Series EUA price

Â

Â

Â

Coal Price ARA

Monthly Coal prices for the Amsterdam Rotterdam Antwerp area were downloaded from DataStream. As approximation the â€œDRI-WEFA Steam Coal ARA Indexâ€ was used

Time Series	Description
COAL_ARA_LR	Coal ARA index, monthly, as 1st differences logarithms

Table 5â€‘3: Time Series Coal price

Â

Gas Price NBP

UK Natural Gas, 1-Day Forward, ICE Natural Gas 1 Month Forward and the London Natural Gas Index as daily time series will be used in order to check for the influence of gas on the emissions price.

Time Series	Description
NATDGAS_LR	UK Natural Gas,1 Day Forward P/Therm, as 1st differences logarithms
NATBGAS_LR	ICE Natural Gas 1 Mth.Fwd. P/Therm, as 1st differences logarithms
LONDONNGINDX_LR	London Natural Gas Index P/Therm – PRICE INDEX, as 1st differences logarithms

Table 5â€‘4: Time Series Gas price

Â

Oil price

The relationship with the Oil price will be examined using daily series of Crude Oil-Brent Dated FOB and Crude Oil-Brent Cur. Month Futures.

Â

Time Series	Description
BRENT_DATED_LR	Crude Oil-Brent Dated FOB U$/BBL, as 1st differences logarithms
BRENT_CM_LR	Crude Oil-Brent Cur. Month FOB U$/BBL, as 1st differences logarithms

Table 5â€‘5: Time Series Crude Oil price

Â

Â

Weather

Because I could not get hold of an average temperature and rainfall for Europe, the average was constructed by using the following 9 weather stations: Stockholm, Oxford, Schiphol, Berlin, Paris, DÃ¼sseldorf, Rome, Madrid and Cordoba. [65] Temperature and precipitation were available until

31/07/2006.

In each stationâ€™s time series missing precipitation data was set to 0,00001 and for missing temperature data the data of the previous day was used.

Heating and Cooling degree-days were calculated according to the US-Method. This method reports the absolute deviation of the dayâ€™s average temperature to 18Â°C. A temperature of â€“5Â°C would then result in a number of 18-(-5)=23. The theory behind it is that when the temperature is below 18Â°C people would switch their heating on and when it is above cooling would be needed.

For both precipitation and HDD+CDD an equally weighted time series and one time series weighted by the verified emissions of each weather stationâ€™s country were generated.Â Logarithmic differences where used to obtain a series, which contains the changes in temperature.

After estimating a regression with just the price of EUAs and the logarithmic differences it became obvious that this relationship was not very strong. (RÂ^2 = 0.0012)

Assuming that market participants would trade EUAs today rather on the weather outlook for last week than past weather data, the weather data was transformed to resemble a 5-day weather forecast. This was done using the following formula: $HCDD_t$ = log($HCDD_{t+5}$) â€“ log($HCDD_{t+4}$)

After estimating the regression on the newly created time series the RÂ^2 increased substantially to 0.0069. Therefore precipitation and HDD+CDD will used as a forecast in the following.

Â

Time Series	**Description**
HCDD_EQ_LRF	Heating and Cooling Degree Days, equally weighted, as 1st differences logarithms
PREC_EQ_LRF	Precipitation, equally weighted, as 1st differences logarithms
HCDD_W_VE_LRF	Heating and Cooling Degree Days, verified emissions weighted, as 1st differences logarithms
PREC_W_VE_LRF	Precipitation, verified emissions weighted, as 1st differences logarithms

Table 5â€‘6: Time Series Weather data

Â

5.4Â Â Â Â Â Application of the methodology

5.4.1Â Â Â Â Â Â Â Unit Root test

The augmented Dickey-Fuller test and the Phillips Perron test were used to test each time series of the presence of unit root. The number of lags used in this test was determined automatically by Eviews with respect to the Schwarz Information Criterion (SIC).

Â

H_0	Series is non-stationary, unit root is present

H_1	Series is stationary, unit root is not present
Significance Level	5%

Table 5â€‘7: Hypothesis Dickey Fuller Test

Â

It can be seen from Table 5â€‘8 that at a 5% significance level we can reject the Null Hypothesis in favour of the alternative. None of the time series contained unit root in the Augmented Dickey Fuller and the Phillips Perron Test and therefore they can be used in further analysis as they are.

Â

Â	**First differences**			**Level**		
Series	**Lag length (SIC)**	**ADF test statistic**	**Test critical values: 5%**	**Bandwidth**	**Phillips Perron**	**Test critical values: 5%Â**
EEXEUAS_LR	0	-15.71206	-2.869198	8	-15.85689	-2.869198
BRENT_CM_LR	0	-23.76722	-2.866879	2	-23.75999	-2.866879
BRENT_DATED_LR	0	-22.99810	-2.866879	2	-22.99749	-2.866879
HCDD_EQ_LRF	0	-21.24989	-2.868387	24	-24.67523	-2.868387
HCDD_W_VE_LRF	0	-21.94218	-2.868387	26	-27.11189	-2.868387
LONDONNIGINDX_LR	0	-24.04558	-2.866879	4	-24.03244	-2.866879
NATBGAS_LR	0	-21.83668	-2.866879	14	-22.15042	-2.866879
NATDGAS_LR	0	-22.79697	-2.866879	6	-22.86390	-2.866879
PREC_EQ_LRF	2	-18.08788	-2.868422	135	-170.2490	-2.868387
PREC_W_VE_LRF	2	-17.94235	-2.868422	122	-167.4299	-2.868387
Monthly Series	Â	Â	Â	Â	Â	Â
EEXEUAS_LRM	0	-3.676312	-3.065585	2	-3.676844	-3.065585
COAL_ARA_LR	0	-3.739066	-2.991878	4	-3.608858	-2.991878

Table 5â€‘8: Results of ADF tests

Â

5.4.2Â Â Â Â Â Â Â Granger Causality test

Pairs of the EUA price together with each underlying factor were formed and then tested for granger causality.

H_0	X does not granger cause Y
H_1	X does granger cause Y
Significance Level	5%

Table 5â€‘9: Hypothesis Granger Causality Test

Â

The pairs of variables were put pair wise in Vector Autoregression Models to determine the optimal number of lags with Eviews â€œlaglenâ€ function. Since the Schwarz criterion resulted in most of the pairs in a lag length of only 0 or 1 lags, it was decided to use the less restrictive Akaike criterion.

The probabilities (p-value) reported in the following table indicate the lowest significance level at which a null hypothesis can be rejected. When testing at a 5% significance level the H_0 cannot be rejected at probabilities greater than 0.05.

X	**Lags**	**X does not cause EEXEUAS_LR**		**EEXEUAS_LR does not cause XÂ**	
Â	**Â**	**F-Statistic**	**Probability**	**F-Statistic**	**Probability**
BRENT_CM_LR	1	0.47849	0.48955	0.08714	0.76802
BRENT_DATED_LR	1	1.07051	0.30152	0.01985	0.88803
HCDD_EQ_LRF	3	1.63363	0.18128	3.76408	**0.01105**
HCDD_W_VE_LRF	4	2.51496	**0.04137**	1.45782	0.21465
LONDONNGINDX_LR	2	0.09826	0.90644	0.74879	0.47367
NATBGAS_LR	1	1.71968	0.19056	0.00160	0.96811
NATDGAS_LR	1	0.04812	0.82649	0.00893	0.92477
PREC_EQ_LRF	14	0.87780	0.58355	1.68123	0.05823**Â**
PREC_W_VE_LRF	10	0.95369	0.48404	1.92246	**0.04145**
Â	Â	Â	Â	Â	Â
COAL_ARA_LR	1*	3.58876	0.08063	0.21598	0.64981

Table 5â€'10: Probabilities Granger Causality Test

*For the testing with monthly coal prices a lag length of 1 was chosen as reasonable, because it is assumed that coal prices older than one month would not affect the current emissions price.

Â

5.5Â Â Â Â Â Conclusion / Main Findings

After testing the data, Table 5â€'10 shows that we can reject the null that â€œHCDD_W_VE_LRF does not cause EEXEUAS_LRâ€ in favour of the alternative at 5% significance level. Therefore we can say that the 5 days Heating and Cooling degree day forecast Granger causes the price of EUAs. This variable represents the Heating and Cooling Degree days weighted by the verified emissions of the country where the weather station is located.

Â

At 5% significance level we can also reject the null that â€œEEXEUAS_LR does not Granger cause HCDD_EQ_LRFâ€ and that â€œEEXEUAS_LR does not Granger cause PREC_W_VE_LRFâ€ but a EUA price causing temperature or rainfall does not make any sense. Therefore these relationships will be ignored.

When relaxing to a 10% significance level on the monthly series, we can reject the Null that â€œCOAL_ARA_LR does not cause EEXEUAS_LRâ€. In this case we could also include Coal prices as a factor that causes the price of EUAs.

In conclusion it can be said that only Heating and Cooling degree days weighted by verified emissions are Granger causing the EUA price at 5% significance level. On a monthly basis at 10% significance level it can further be said that Coal prices are Granger causing the EUA price.

For the other fuels and precipitation a statistically significant Granger Causality could not be found.

Â

6Â Â Â Â Â Â Â Â Possible Future research

When there is more data available and the JI has started to take off an analysis could be undertaken to find out how the allowances generated by projects will affect the EUA price. It should then also be considered that a high EUA price might incentive investment in CDM/JI as a substitute to buying EUAs.

Another possible research could be undertaken between country ratings and the price of emissions credits generated in those countries. How much of the credit price is explained by the project risk and how much by the country risk.

Lastly it could be interesting to look at the opportunities for companies in the EU ETS and under the Kyoto protocol in the context of a real option evaluation.

Â