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Predicting the Price of EU ETS Carbon Credits

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Abstract

The aim of this paper is to examine what drives the changes in price of carbon credits in the European Union's Emission Trading Scheme (EU ETS) and to make predictions based on these relationships. The study is based on dataset from the United Kingdom (UK) energy market and global equity indices. The large dataset is reduced in dimension using correlation analysis and predictions are then made by multiple linear regression. Certified emission reduction units (CERs) are shown to be the only same-day market relationship which provides useful predictions of European Union Allowance prices (EUAs). No significant correlation is found between EUAs and the UK power market and the theoretical price of carbon credits; switching price, is shown to be a poor indicator of the price of carbon credits.

Keywords: EU ETS; Carbon Credits; Correlation Analysis

1. Introduction

The increased concentration of greenhouse gases in the atmosphere is now a generally accepted fact among scientists. More important is the consensus that the concentration is largely due to human activity and that the increased concentration is directly linked to the phenomena of global warming and climate change [1]. Should no action be taken, the earth's average surface temperature could rise by 4°C by the year 2100, which could result in catastrophic effects. To address this risk, countries of the world gathered for the Earth Summit in Rio de Janeiro in 1992 and agreed on an international treaty; the United Nations Framework Convention on Climate Change (UNFCCC). The aim of the treaty was to slow down greenhouse gas emissions and the convention addressed important issues of climate change mitigation, new technology and promoting education. The treaty was however not legally binding so in 1997 an addition to the treaty was adopted, known as the Kyoto Protocol. According to the Kyoto Protocol, overall emissions will be reduced by five percent compared to 1990 levels over the period from 2008 to 2012, known as the Kyoto commitment period. Following the Kyoto Protocol the European Union (EU) began preparing an EU carbon market to facilitate EU Member States to meet their commitments in a cost-effective way. On January 1st 2005 the European Union Emission Trading Scheme (EU ETS), the first international trading system of its kind, was launched. The EU ETS is a cap and trade system where overall emission levels are capped but members are free to buy or sell emission allowances as needed. It is currently the largest multi-country, multi-sector emission trading scheme in the world where trading in 2009 accumulated to over $ 118 billion.

Understanding the market and its key price-drivers is essential for managing large-scale investment choices as well as successfully planning existing operations, especially in the energy intensive industrial sector. As exact

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predictions on the market are virtually impossible, knowledge of what drives changes in the price of carbon credits is extremely valuable in constructing optimal hedging and investment strategies. Although the theoretical foundation of carbon markets is widely acknowledged, empirical studies have only been published recently or are forthcoming.

Taschini & Paolella [2] focused on the econometric modeling of the allowances. They conducted an analysis of the statistical distribution of emission trading allowances and constructed GARCH-models to address the tail behavior and heteroskedastic dynamics in the returns. Benz & Truck [3] examined different phases of price and volatility behavior in the returns with the use of Markov switching and AR-GARCH models for stochastic modeling. The models were found to be effective in capturing short-term behavior. Daskalakis et al. [4] compared three main markets under the EU ETS: Powernext, Nord Pool and ECX and concluded that spot prices were better approximated by Geometric Brownian motion augmented by jumps as the spot prices are likely to be characterized by jumps and non-stationarity. Uhrig-Homburg & Wagner [5] examined the relationship between spot and futures markets in the EU ETS and concluded that futures markets lead the price discovery process of carbon credits. The above analyses are however based on data from phase I of the market environment, i.e. from 2005-2007.

Bataller et al. [6] analyzed the effect of different factors on the price of allowances, including weather. They concluded that the most emission intensive energy sources were the principal factors in the determination of carbon prices and that only extreme temperatures could influence the prices. Alberola et al. [7] came to a similar conclusion stating that EUA spot prices not only react to energy prices, but also to unanticipated temperature changes during colder events. In a Master's thesis, Obermayer [8] explored the relationship between carbon credits and German energy complex assets, including electrical power, coal, natural gas and oil. He found power to be the only significant correlation to EUAs and suggested further work on British data. Frunza et al. [9] showed that energy, natural gas, oil, coal and equity indices acted as major factors in driving the carbon allowance prices. They then used an arbitrage pricing model via a hidden Markov chain model to predict futures prices and found the model to be effective both in and out-of-sample.

To this date limited analyses have been done focusing on UK energy data, despite the fact that the United Kingdom is the second largest emitter of the EU countries included in the EU ETS, after Germany[10]. In this paper the drivers behind the changes in price of carbon credits in the EU ETS are examined and EUA price predictions are made based on data from the UK energy market and equity markets.

2. Theoretical framework

The analysis of the data is based on established statistical methods for time series analysis and correlation [11]. The multiple linear regression is based on Montgomery & Runger [12] and Gujarati & Porter [13]. A classical Gaussian standard linear regression model is applied in order to obtain a best linear unbiased estimator defined by the assumptions underlying the Gauss-Markov theorem.

2.1. Model definition

To define the regression model let again $X = x_{i1}, x_{i2}, \ldots, x_{ip}$, $i = 1,2,\ldots,N$, be a vector of p random variables each having N observations and let Y be the dependent variable, also of N observations. The linear relationship between X and Y can be defined by

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} \qquad i = 1,2,\ldots N \tag{1}$$

where $\beta_0, \beta_1, \ldots, \beta_p$ are constants, to be estimated, that assign weights to the regressors. The relationship is however rarely strictly linear so an error term is added

$$y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon_i \qquad i = 1,2,\ldots,N \tag{2}$$

called a multiple linear regression model with p regressors, where the error term, ϵ_i, is a random error with mean zero and an unknown variance σ^2. Using matrix notation the model can be expressed as

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon} \tag{3}$$

where the first column of $\boldsymbol{X}$ is the column vector **1**. Although the model is called a linear regression model it can accommodate non-linear terms such as the interaction term $\beta_{12}X_1X_2$ by simply setting $\beta_{p+1} = \beta_{12}$ and $X_{p+1} = X_1X_2$. In fact, any regression model whose parameters are linear is a linear regression model regardless of the shape of the generated plane.

In order to find the "best fit" to the data an estimation of the betas, denoted by $\widehat{\boldsymbol{\beta}}$, needs to be made. The method of ordinary least squares (OLS) or sum of squared errors can be used to estimate the regression parameters (betas). The goal is to minimize the least squares function L

$$L = \sum_{i=1}^{N} \epsilon_i^2 = \boldsymbol{\epsilon}'\boldsymbol{\epsilon} = (\boldsymbol{y} - \boldsymbol{X\beta})'(\boldsymbol{y} - \boldsymbol{X\beta}) \tag{4}$$

The least squares estimator $\widehat{\boldsymbol{\beta}}$ is then found by taking the partial derivatives of L and finding the minimum

$$\frac{\partial L}{\partial \boldsymbol{\beta}} = \mathbf{0} \tag{5}$$

Equation (5) yields the equations that must be solved

$$\boldsymbol{X}'\boldsymbol{X}\widehat{\boldsymbol{\beta}} = \boldsymbol{X}'\boldsymbol{y} \tag{6}$$

Multiplying both sides of equation (3.30) by $(\boldsymbol{X'X})^{-1}$ then gives the least squares estimate of the betas

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{y} \tag{7}$$

The fitted model can then be represented as $\widehat{\boldsymbol{y}} = \boldsymbol{X}\widehat{\boldsymbol{\beta}}$. The difference between the actual observations and the fitted values is known as the error or residual defined by

$$\boldsymbol{e} = \boldsymbol{y} - \widehat{\boldsymbol{y}} \tag{8}$$

2.2. Significance Testing: The t-statistic and White's robust t-statistic

When an estimate of the betas has been found it is often desirable to verify the significance of the estimated parameters. This can be done using the t-test statistic. To test whether an individual regression coefficient, β_j, equals a value βj_0 the hypothesis $H_0 = \beta_j = \beta_{j0}$ and $H_1 = \beta_j \neq \beta_{j0}$ is tested with the statistic

$$T_0 = \frac{\widehat{\beta}_j - \beta_{j0}}{\sqrt{\sigma^2 C_{jj}}} \tag{9}$$

where C_{jj} is the diagonal element of the inverse of the covariance matrix of $\boldsymbol{X}$, $(\boldsymbol{X'X})^{-1}$, corresponding to the estimated beta, $\widehat{\beta}_j$. The null hypothesis is rejected if $/t_0/ > t_{\alpha/2,n-(p+1)}$.

Significance testing is based on the assumptions of normally distributed, homoskedastic residuals. The homoskedasticity assumption is often hard to meet, rendering the parameter confidence intervals unreliable. White [14] offered a remedy called a heteroskedasticity-consistent covariance matrix estimator to treat heteroskedastic residuals in a manner that yields reliable confidence intervals of the estimator without changing the regression coefficients. Furthermore the estimator holds regardless of the shape of the heteroskedasticity of the residuals. White's robust t-statistic, *HC0*, is defined as

$$HC0 = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\mathrm{diag}[e_i^2]\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1} \tag{10}$$

where the entries on the main diagonal of *HC0* are the estimated squared standard errors of the regression coefficients. Dividing the regression coefficients by these standard errors gives a ratio that can be used to derive the p-values for hypothesis testing [15].

According to [15] a weighted version of White's t-statistic is more reliable. The *HC4* statistic was introduced by Cribari-Neto [16] and is defined as

$$HC4 = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\mathrm{diag}\left[\frac{e_i^2}{(1-h_{ii})^{\delta_i}}\right]\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1} \tag{11}$$

where

$$\delta = \min\left\{4, \frac{Nh_{ii}}{p+1}\right\} \tag{12}$$

where $h_{ii} = \boldsymbol{x}_i(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{x}_i'$. The $h_{ii}s$ are the diagonal elements in the "hat" matrix $\mathbf{H} = \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'$ and also know as leverage values . The δ controls the level of discounting for the *i*th observation with the truncation point at 4. The *p*-values can be extracted from *HC4* in the same way as for *HC0* [15].

2.3. Model Adequacy Checking

After a model has been fitted to data there is no guarantee that the model adequately describes the relationships between the variables. It is interesting to examine how much of the variation in the data is absorbed by the error terms. There are many means to this end but four will be examined for the sake of the analysis, the coefficient of determination, R^2, the adjusted coefficient of determination, R^2_{adj}, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

The coefficient of determination is a measure of how much variation of the dependent variable is explained by the model. The basis of R^2, lies in the concept of analysis of variance (ANOVA) which is mainly comprised of three concepts: the error sum of squares, SS_E, the regression sum of squares, SS_R and the total corrected sum of squares, SS_T. Where,

$$SS_E = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{13}$$

$$SS_R = \hat{\boldsymbol{\beta}}'\boldsymbol{X}'\boldsymbol{y} - \frac{\left(\sum_{i=1}^{N} y_i\right)^2}{N} \tag{14}$$

$$SS_T = \boldsymbol{y}'\boldsymbol{y} - \frac{\left(\sum_{i=1}^{N} y_i\right)^2}{N} \tag{15}$$

For a linear model the sums are connected by relationship $SS_T = SS_E + SS_E$. Furthermore the quantity $MS_E = SS_E/(N-p)$ is called the error mean square or mean squared error. Using the above relationship the coefficient of determination is defined as

$$R^2 = 1 - \frac{SS_E}{SS_T} = \frac{SS_R}{SS_T} \tag{16}$$

This statistic should however be used with caution. Generally R^2 increases every time a new variable is added to the model but that does not always imply a better model. Adding new variables to the model incurs a loss of one error degree of freedom meaning that in order for the model to be superior the error sum of squares of the new model should be reduced by an amount equal to the original error mean square. To counter this tendency an adjusted version of R^2 exists, where

$$R^2_{adj} = 1 - \frac{SS_E/(N-p)}{SS_T/(N-1)} = 1 - \frac{MS_E}{SS_T/(N-1)} \tag{17}$$

Equation (17) states that the adjusted coefficient of determination will only increase if the error mean square is reduced when a new variable (increased value of p) is added to the model, therefore R^2_{adj} is a good guard against overfitting.

The AIC and BIC statistics are also measures of goodness of fit and can be said to describe the tradeoff between bias and variance. Both punish for including more parameters in the model but BIC includes a larger penalty for overfitting. The AIC and BIC are defined as follows:

$$AIC = N \log\left(\frac{SSE}{N}\right) + 2p \tag{18}$$

$$BIC = N \log\left(\frac{SSE}{N}\right) + p \log(N) \tag{19}$$

where p stands for number of variables and N is the number of observations or data points. When comparing models by their respective AIC and BIC, the model having the lowest value is considered the best model in terms of AIC and BIC.

3. Data

The analysis aims at testing a large dataset of various time series using dimension reduction techniques to gain a-priory knowledge for regression modeling. It is known that traders targeting carbon closely follow energy, as well as commodities such as brent crude oil, gasoil, natural gas, coal and sometimes also equity indices. Table 1 shows the chosen data for the analysis, their source as well as the period available. Since the aluminum industry will be included in phase III of the EU ETS, LME aluminum prices are included in the database. A weather index is also included since other analyses have concluded that weather may be a factor in EUA prices as mentioned in the introduction.

Table 1: The data chosen for the analysis (Source: Bloomberg).

Time Series	Quoted unit	Data
EUA Spot	EUR/Metric ton	24.6.2005-22.10.2010
CER futures	EUR/Metric ton	14.3.2008-22.10.2010
WTI crude futures		3.2.2006-22.10.2010
Gasoil futures		4.1.2005-22.10.2010
Natural gas futures	p/therms	4.1.2005-22.10.2010
Electricity Base Load	GBP/MWh	4.1.2005-22.10.2010
Electricity Peak Load	GBP/MWh	4.1.2005-22.10.2010
Brent crude oil		4.1.2005-22.10.2010
Coal	USD/Metric ton	10.9.2007-22.10.2010
Aluminum Primary	USD/ton	4.1.2005-22.10.2010
Aluminum Alloy	USD/ton	4.1.2005-22.10.2010
Dark Spread	EUR/MWh	11.09.2007-22.10.2010
Clean Dark Spread	EUR/MWh	11.09.2007-22.10.2010
Spark Spread	EUR/MWh	4.1.2005-22.10.2010
Clean Spark Spread	EUR/MWh	4.1.2005-22.10.2010
Switching Price	EUR/Metric ton	11.09.2007-22.10.2010
Weather	Index	7.2.2008-22.10.2010
Nasdaq 100 Index	Index	4.1.2005-22.10.2010
Standard & Poor's 500 Index	Index	4.1.2005-22.10.2010
FTSE 100 Index	Index	4.1.2005-22.10.2010
Deutscher Aktien Index	Index	4.1.2005-22.10.2010
Compagnie des Agents de Change	Index	4.1.2005-22.10.2010
Amsterdam Stock Exchange	Index	4.1.2005-22.10.2010
Portuguese Stock Index	Index	4.1.2005-22.10.2010
USD/GBP	Currency	4.1.2005-22.10.2010
USD/EUR	Currency	4.1.2005-22.10.2010
EUR/GBP	Currency	4.1.2005-22.10.2010

4. Results

4.1. *Data distribution*

The distribution of EUA returns is shown in Table 2. The mean of the returns is negative over the duration of the period in question. The standard deviation is high relative to equity indices, indicating high volatility, and the positive skewness indicates that the distribution is skewed to the right, meaning that the right tail of the distribution is somewhat longer. The distribution has heavier tails than a normal distribution since the excess kurtosis is close to one.

Table 2: The first four moments of the EUA data set.

	Mean	Standard deviation	Skewness	Kurtosis	Excess kurtosis
EUA	-0.0015	0.0319	0.0913	3.9285	0.9285

A graphical representation of the results in Table 2, are shown in figure 1. The histogram (left) shows the actual EUA returns with a fitted normal curve. The positive skew is not obvious but the heavier tails are more apparent. Plotting the sample quantiles of EUAs (right) versus theoretical quantiles from a normal distribution also shows that the returns are not normally distributed. The slight s-shaped curve formed by the EUA returns indicates heavier tails. EUA returns indicate heavier tails.

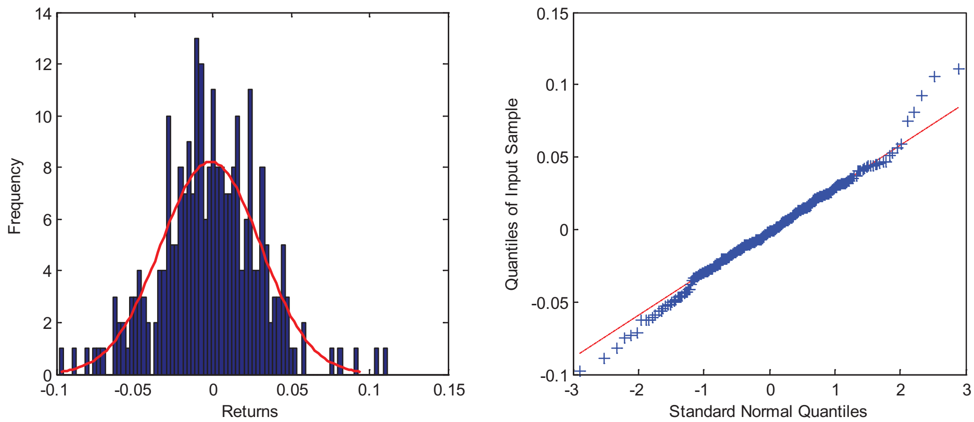

Fig. 1 A histogram of EUA spot returns with a fitted normal probability density function (PDF) (left) and a qq-plot of the sample quantiles of EUAs shown in blue versus theoretical quantiles from a normal distribution, shown in red (right).

4.2. *Correlation analysis*

Correlations of the sample data were analyzed for same-day as well as 1 business day lagged values. Correlations were low for values lagged by one business day and onward. Top ten correlations to EUA returns are shown in Table 3.

Same-day correlation is strongest in particularly the correlation between EUAs and CERs. The next three highest correlations are all equity indices. Moving to lag-1 business day, the correlations have fallen substantially. CERs, which formerly had the greatest correlation to EUAs now show low correlation. Reaching the lag of one business week all correlations are weak.

The autocorrelation of EUAs was also examined. As shown in figure 2 no substantial autocorrelation was found. Most points are within the confidence limit and no pattern is visible. The autocorrelation of the remainder of the training data set was examined using a visual inspection as seen in the figure 2 below. No substantial autocorrelation was found.

Based on correlations the top five variables of each lag were chosen as input variables into a baseline regression model, i.e. the top five correlations to EUA returns of each column in Table 3.

Table 3: The data chosen for the analysis

Same-day		Lag-1 business day	
EUA	1.00	EUA	1.00
CER	0.91	CER	0.17
CAC	0.40	NDX	0.17
PSI20	0.40	SPX	0.15
DAX	0.38	Weather	-0.14
Gasoil	0.37	EUR/GBP	0.09
UKX	0.37	Gasoil	-0.09
WTI crude	0.36	WTI crude	0.08
Brent crude	0.32	Coal	0.07
CDS	0.32	Natural gas	0.07
AL Primary	0.27	USD/GBP	0.07

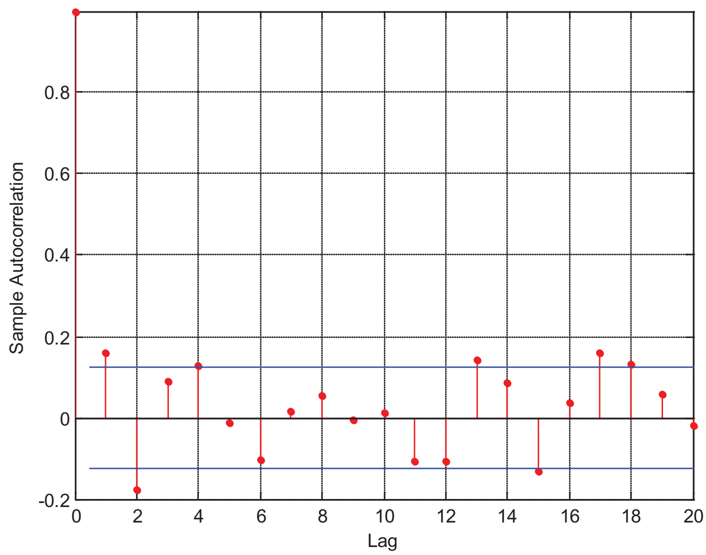

Fig. 2 Autocorrelation of EUA returns from zero to twenty lags. The red dots indicate the value of the correlation and the blue lines represent the confidence level of two standard deviations or approximately 95%

4.3. Base line regression

As a mean of comparison the base-line regressions were set using correlation as the dimension reduction technique. Regressions were done on same-day data as well as data lagged by one day. The same-day results are shown in Table 4. The only variable whose adjusted p-value (HC4) was within the confidence interval of 95% (p-value below 0.05) was CER. The regression was therefore repeated using only CERs plus a constant as regressors. The results are shown in Table 5. There seems to be a strong same-day relationship between EUA returns and CERs as the model captures over 80% of the variability of EUAs.

Table 4: Base-line regression results for same-day training data.

Variable	β	t-stat	p-value	HC4	p HC4-value
Constant	-6.7119 E-06	-0.0082	0.9935	-0.0082	0.9935
CER	0.8874	30.5127	4.2736 E-86	27.3495	5.6866 E-77
CAC	0.0446	0.5004	0.6172	0.4133	0.6797
PSI20	0.0286	0.3746	0.7083	0.3322	0.7400
DAX	0.0132	0.1780	0.8588	0.1296	0.8970
Gasoil	0.0534	1.7734	0.0774	1.8723	0.0623
Goodness	MSE	R^2	R^2_{adj}	AIC	BIC
of fit	1.7134 E-04	83.50%	83.17%	-2,161	-2,062

Table 5: Base-line regression results for same-day training data after adjustment.

Variable	β	t-stat	p-value	HC4	p HC4-value
Constant	-0.0015	-0.0785	0.9375	-0.0789	0.9372
CER	0.9296	34.8001	1.9622E-98	33.8877	4.9931E-96
Goodness	MSE	R^2	R^2_{adj}	AIC	BIC
of fit	1.7668E-04	82.72%	82.65%	-2,150	-2,050

The residuals of the model were stationary but did not pass a normality test and a qq-plot showed heavy set tails, indicating higher probability of extreme events. They also showed some degree of heteroskedasticity. The adjusted t-statistic (HC4) is however heteroskedasticity consistent. No signs of autocorrelation could be detected. Figure 3 shows the results of Table 5 graphically. Since the EUA returns are not strictly normal and some number of outliers is present in the heavy tails, the above results were compared to the results of a robust regression. The robust regression yielded similar results and the influence of extremities therefore rejected.

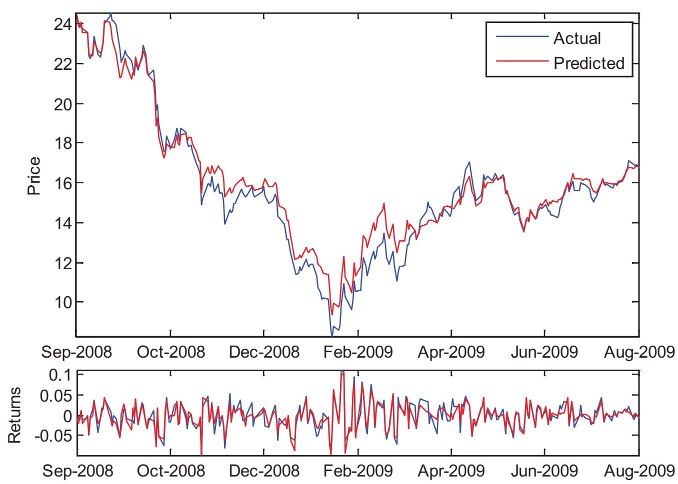

Fig. 3: The actual vs. predicted same-day price and returns for EUAs using the base-line model.

5. Summary

The study shows that correlation generates a dataset of equity indices along with CERs, which are highly correlated to EUAs. The reduced dataset generated by correlation analysis on same-day data is shown to be a useful input for a multiple linear regression model. Same-day correlations, highlighting CERs, provide a dataset of good predictors of EUA price development but all correlations are low when data is lagged by one business day and the regression model fails to provide useful predictions. No significant correlation is found between EUA returns and electricity returns.

Future research will look at other statistical methods such as the principal component analysis (PCA) and latent root analysis to identify the principal components affecting the carbon price. A price model based on such analysis could give better results than present correlation approach.

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