Economics Bulletin

Volume 30, Issue 1

# EUAs and CERs: Vector Autoregression, Impulse Response Function and Cointegration Analysis

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## Abstract

EUAs are European Union Allowances traded on the EU Emissions Trading Scheme (EU ETS), while Certified Emissions Reductions (CERs) arise from the Clean Development Mechanism under the Kyoto Protocol. These emissions assets attract an increasing attention among brokers, investors and operators on emissions markets, because they may be both used for compliance under the EU ETS (up to fixed limits). This paper proposes a statistical analysis of the inter-relationships between EUA and CER price series, by using vector autoregression, impulse response function, and cointegration analysis on daily data from March 9, 2007 to January 14, 2010. The central results show that EUAs and CERs affect each other significantly through the vector autoregression model, and react quite rapidly to shocks on each other through the impulse response function analysis. Most importantly, both price series are found to be cointegrated, with EUAs leading the price discovery process in the long-term through the vector error correction mechanism.

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**Citation:** Julien Chevallier, (2010) "EUAs and CERs: Vector Autoregression, Impulse Response Function and Cointegration Analysis", *Economics Bulletin*, Vol. 30 no.1 pp. 558-576.
**Submitted:** Jan 18 2010. **Published:** February 17, 2010.

# 1 Introduction

The EU ETS is the cornerstone of European climate policy. It distributes to industry a fixed quota of carbon emissions permits, which trade at a certain carbon price. EUAs (EU Allowances) are the tradable unit under the EU ETS. The scheme allows companies a cheap alternative way to meet their carbon caps, buying Certified Emissions Reductions (CERs) from developing countries, funding emissions cuts there instead[1]. Primary CERs (pCERs) are purchases direct from projects. Secondary CERs (sCERs) are free of project risks and traded on exchanges. We choose to focus in this paper on sCERs, since pCERs carry a high degree of delivery risk which is currently not priced on exchanges. Albeit being determined on distinct emissions markets, sCERs and EUAs may be exchanged based on their representative trading unit. One sCER is indeed equal to one ton of $CO_2$-equivalent emissions reduction, while one EUA is equal to one ton of $CO_2$ emitted in the atmosphere.

This paper develops - to our best knowledge - the first statistical anaylsis of the price relationships between EUAs and sCERs, which are both fungible under the EU ETS.[2] While both EUAs and sCERs prices influence each other statistically, as shown by vector autoregressive modeling and Granger causality tests, our central results identifies the existence of one cointegrating relationship between EUAs and sCERs prices by using daily data from March 9, 2007 to January 14, 2010. Therefore, we are able to conclude that the EUA price is the leader in the long-term price discovery. This result may be explained by predominant role of the EU ETS, which is the most developed and liquid emissions market to date. The existence of a price difference of EUAs and the market for secondary CERs could be explained by the existence of various risk-premia embedded in sCERs compared to holding EUAs.

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 provides unit root tests. Section 4 describes the vector autoregressive structure between EUA and sCER prices. Section 5 presents cointegration results. Section 6 concludes.

# 2 Data

For EUAs, we use futures prices with a daily frequency. The most liquid platform for futures prices is the European Climate Exchange (ECX). For sCERs, we work with the Reuters CER price index, which is available since March 9, 2007. Our dataset ends on January 14, 2010. Our sample contains 729 daily observations for both price series. As is common practice (Carchano and Pardo (2009)), we roll over the futures contracts of various maturities.

The time-series of EUA and sCER prices are pictured in Figure 1. EUAs were trading at €15 in March 2007, then stayed in the range of €19-25 until July 2008, and decreased steadily afterwards to achieve €8 in February 2009. sCERs started at €12.5 in March 2007, evolved in the range of €12-22 through July 2008, and continued to track EUA prices until €7 in February 2009. We observe that the sCER price evolution is not completely independent of EUA prices: the sCER price seems to be computed with a risk-premium from EUA prices. On January 14, 2010, sCERs traded at 11.78€, while EUAs traded at 13.60€. Table 1 provides descriptive statistics.

[1]According to the article 12 of the Kyoto Protocol, projects under the Clean Development Mechanism consist in achieving greenhouse gases emissions reduction in non-Annex B countries. After validation, the United Nations Framework Convention on Climate Change (UNFCCC) delivers credits that may be used by Annex B countries for use towards their compliance position.

[2]Indeed, the EU Linking Directive allows the import for compliance into the EU ETS up to 13.4% of CERs on average.

# 3 Unit Root Tests

In this section, we develop standard unit root tests that we apply to both EUAs and sCERs price series. Dickey-Fuller (1979) test the nullity of the coefficient $\alpha$ in the following regression:

$$\Delta x_t = x_{t+1} - x_t = \alpha x_t + \beta + e_t$$

- if $\alpha$ is significantly negative, then we say that the process $x_t$ has no unit root, or that it is stationary, inducing a mean-reverting behavior for the prices;

- if $\alpha$ is not significantly different from 0, then we say that the process $x_t$ 'has a unit root', inducing a random walk behavior for the prices.

In practice, Augmented-Dickey-Fuller (ADF, 1981) or Phillips-Peron (PP, 1988) tests are used rather than Dickey-Fuller. These tests are based on the same principle but correct for potential serial autocorrelation and time trend in $\Delta x_t$ through a more complicated regression :

$$\Delta x_t = \sum_{i=1}^{L} \beta_i \Delta x_{t-i} + \alpha x_t + \beta_1 t + \beta_2 + e_t$$

The ADF test tests the null hypothesis $H_0$ that $\alpha = 0$ (the alternative hypothesis $H_1$ being that $\alpha < 0$) by computing the Ordinary Least Squares (OLS) estimate of $\alpha$ in the previous equation and its $t$-statistics $\hat{t}$; then, the statistics of the test is the t-statistics $\hat{t}_\alpha$ of coefficient $\alpha$, which follows under $H_0$ a known law (studied by Fuller and here denoted $Ful$). The test computes the $p$-value $p$, which is the probability of $Ful \leq \hat{t}$ under $H_0$. If $p < 0.05$, $H_0$ can be safely rejected and $H_1$ accepted: we conclude that the series '$x_t$ has no unit root'. Extensions of these stationarity tests were also developed by Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992).

We report the ADF, PP, and KPSS tests for EUA and sCER prices in Tables 2 and 3, respectively. From these tests, we conclude that both price series are integrated of order 1 (I(1)), *i.e.* when they are stationary when transformed to first-differences.

# 4 Vector AutoRegressive Model

The traditional model for studying correlated stationary prices is the Vector-Auto-Regressive model (VAR), which is the multi-variate extension of the AR model (Watson (1994)).

## 4.1 VAR Model Representation

Let $Z_t = \begin{pmatrix} X_t^1 \\ X_t^2 \end{pmatrix}$ be the vector process formed of the two (properly transformed to stationary) EUA and sCER prices. Then, the VAR($p$) model reads :

$$Z_t = C + \Gamma_1 Z_{t-1} + \ldots + \Gamma_p Z_{t-p} + \epsilon_t$$

where $C = \begin{pmatrix} C^1 \\ C^2 \end{pmatrix}$ is a constant vector, $\Gamma_1, \ldots, \Gamma_p$ are 2x2 matrices and the vector process $\epsilon_t = \begin{pmatrix} \epsilon_t^1 \\ \epsilon_t^2 \end{pmatrix}$ is formed of independent random variables following a centered bi-variate normal distribution $N(0, \sum)$.

## 4.2 Parameters estimation

The calibration of the model VAR($p$) proceeds in three classic steps:

1. the optimal order $p$ is selected using an information criterion, which is an indicator of the relevance of a model, giving a positive weight to the likelihood of the model and a negative weight to the number of model parameters ; e.g., the Schwarz Information Criterion (SIC) is equal to $2LL - ln(T)n$, where $LL$ is the log-likelihood, $T$ is the number of observations and $n$ is the number of parameters of the model.

2. once $p$ is known, $C, \Gamma_1, \ldots, \Gamma_p$ are determined by OLS.

3. lastly, the standard deviation and correlation of the residuals give matrix $\sum$

Based on the SIC, we choose to implement the most parsimonious VAR($p$) model of order 1 (VAR(1)). Table 4 shows Vector Autoregression estimates. We observe that lagged sCER prices impact EUA prices, and that sCER prices are best explained by an AR(1), at the 1% significance level.

## 4.3 Causality in the Granger sense

We will say that a process $P_t^1$ Granger causes $P_t^2$ at the order $p$ if, in the linear regression of $P_t^2$ on lagged prices $P_{t-1}^1, \ldots, P_{t-p}^1, P_{t-1}^2, \ldots, P_{t-p}^2$, at least one of the regression coefficients of $P_t^1$ on the lagged prices $P_{t-1}^2, \ldots, P_{t-p}^2$ is significantly different from 0. The intuition behind Granger causality is that the information on past prices $P_{t-1}^2, \ldots, P_{t-p}^2$ is relevant to forecast $P_t^1$ at future time $t$.

Granger causality is examined using the Granger causality test testing the null hypothesis $H_0$ that all regression coefficients of $P_t^1$ on the lagged prices $P_{t-1}^2, \ldots, P_{t-p}^2$ are null. A $p$-value lower than 0.05 means that $H_0$ can be rejected (and causality accepted) with 95% confidence level.

Table 5 presents pairwise Granger causality tests results. We identify that a positive causality runs from EUA returns to sCER returns, and conversely[3]. Hence, we confirm our analysis that both price series are inter-related. This is also meaningful in an economic context to find that EUAs and sCERs are inter-related, since they both represent the same emissions asset that can be used for arbitrage purposes for compliance within the European trading system[4]. Since Granger causality test results are also useful to determine the order of the Cholesky decomposition in the impulse response function analysis, it thus follows very logically to simulate random shocks in the next section in order to have a better understanding of the interrelationships between the two variables.

## 4.4 VAR Dynamics

Following Granger causality tests, it appears interesting to study further the behaviour of the pairs EUA/sCER through the dynamic structure of the VAR(1) model by performing Impulse Response Function (IRF) analysis (Pesaran and Shin (1998)).

[3]As shown in Table 5, the results obtained are not sensitive to the order of the lag retained for the Granger causality test.

[4]Note this question of arbitrage goes beyond the scope of the present article.

#### 4.4.1 Shocks analysis: Impulse Response Functions

Figure 2 shows the results of the IRF analysis. We observe that both price series react rapidly (at time $t = 2$) and positively to a shock on the other variable in the system. The effects of the initial shock are dampened are time $t = 3$, and disappear at time $t = 5$. EUAs and sCERs therefore exhibit the same pattern in terms of responses to exogenous shocks. Besides, this oscillation towards zero is characteristic of stationary VAR models.

#### 4.4.2 Variance decomposition

We also perform variance decomposition analysis for the pair EUA/sCER. In Figure 3, we observe that the variance of the forecast error of the EUA variable is due to 66% to its own innovations, and to 33% to the innovations of the sCER variable. The variance of the forecast error of the sCER variable is due to 32% to the EUA variable, and to 68% to itself. This graph therefore confirms the statistical influences running both ways between EUA and sCER prices.

# 5 Cointegration Analysis using Johansen's procedure

In this section, we use the concept of cointegration to look for a stationary linear combination of EUA and sCER prices, which will represent the long-run equilibrium. Then, we study the error-correction mechanisms insuring the reversion to the long-run equilibrium.

## 5.1 Conditions for cointegration

First, we have checked in Section 3 based on standard stationarity tests that the prices of EUA and sCER are non stationary and integrated of order one. This amounts to checking that they are difference stationary, i.e. $\Delta X_t^e$ and $\Delta X_t^{e'}$ are stationary. The fact that the series are integrated of the same order is indeed a pre-requisite condition for cointegration.

The next step of the cointegration model consists in describing the dynamics of EUAs and sCERs in terms of the residuals of the long-term relation (Johansen (1988)):

$$\begin{pmatrix} \Delta X_t^e \\ \Delta X_t^{e'} \end{pmatrix} = \begin{pmatrix} \mu_e \\ \mu_{e'} \end{pmatrix} + \textstyle\sum_{k=1}^{p} \Gamma_k \begin{pmatrix} \Delta X_{t-k}^e \\ \Delta X_{t-k}^{e'} \end{pmatrix} + \begin{pmatrix} \Pi_e \\ \Pi_{e'} \end{pmatrix} R_t + \begin{pmatrix} \epsilon_t^e \\ \epsilon_t^{e'} \end{pmatrix}$$

where

- $e$ stands for EUA, and $e'$ stands for sCER;
- $X_t^e$ is the log price of variable $e$ at time $t$;
- the 2x1 vector process $\Delta Z_t = \left(\Delta X_t^e = X_{t+1}^e - X_t^e, \Delta X_t^{e'} = X_{t+1}^{e'} - X_t^{e'}\right)'$ is the vector of EUA and sCER price returns;
- $\mu = (\mu_{X,e}, \mu_{X,e'})$ is the 1x2 vector composed of the constant part of the drifts;
- $\Gamma_k$ are 2x2 matrices expressing dependence on lagged returns;
- $(R_t = X_t^e - \beta X_t^{e'})$ is the process composed of the deviations to the long-term relation between the EUA and sCER log prices;
- $\Pi$ is a 2x1 vector matrix expressing sensitivity to the deviations to the long-term relation between the EUA and sCER prices;
- the residual shocks $(\epsilon_t^e, \epsilon_t^{e'})$ are assumed to be i.i.d with a centered bi-variate normal distribution $N(0, \sum)$.

## 5.2 Cointegration Relation Tests

We need to check here if the EUA and sCER variables are cointegrated, i.e. if $\beta$ exists such that $R_t = X_t^e - \beta X_t^{e'}$ is stationary. This can be done by performing an OLS regression of $X_t^e$ on $X_t^{e'}$ or more rigorously by using the Johansen cointegration test (Johansen and Juselius (1990), Johansen (1991)).

We want to introduce an error-correction mechanism on the levels and on the slopes between the variables $e$ and $e'$.

Let $X_t$ be a vector of $N$ variables, all $I(1)$:

$$X_t = \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \epsilon_t$$

with $\epsilon_t \sim WGN(0, \Omega)$, $WGN$ denotes the White Gaussian Noise, $\Omega$ denotes the variance covariance matrix, and $\Phi_i$ $(i = 1, \ldots, p)$ are parameter matrices of size $(NxN)$.

Under the null $H_0$, there exists $r$ cointegration relationships between $N$ variables, *i.e.* $X_t$ is cointegrated with rank $r$.

The error correction model writes:

$$\Delta X_t = \Pi_1 \Delta X_{t-1} + \ldots + \Pi_{p-1} \Delta X_{t-p+1} + \Pi_p X_{t-p} + \epsilon_t$$

where the matrices $\Pi_i$ $(i = 1, \ldots, p)$ are of size $(NxN)$.

All variables are $I(0)$, except $X_{t-p}$ which is $I(1)$.

For all variables to be $I(0)$, $\Pi_p X_{t-p}$ needs to be $I(0)$ as well.

Let $\Pi_p = -\beta\alpha'$, where $\alpha'$ is an $(r, N)$ matrix which contains $r$ cointegration vectors, and $\beta$ is an $(N, r)$ matrix which contains the weights associated with each vector.

If there exists $r$ cointegration relationships, then $Rk(\Pi_p) = r$. Johansen's cointegration tests are based on this condition.

$$\Delta X_t = \Pi_1 \Delta X_{t-1} + \ldots + \Pi_{p-1} \Delta X_{t-p+1} - \beta\alpha' X_{t-p} + \epsilon_t$$

We computed the trace test statistics and maximum eigenvalue test statistics associated with Johansen's methodology. Table 6 shows the Johansen Cointegration Rank Tests results. Both the Trace test and the Maximum Eigenvalue test indicate the presence of one cointegrating relationship between EUAs and sCERs at the 5% significance level.

## 5.3 Estimation of the Error Correction Model

Table 7 shows the Vector Error Correction Model (VECM) estimated through maximum likelihood methods (Johansen and Juselius (1990), Johansen (1991)). The VECM representation is validated by the fact that both coefficients in the cointegrating equation for EUAs and sCERs are significantly *negative* at the 1% level.

This result illustrates the error correction mechanism which leads towards the long-term stationary relationship between EUAs and sCERs. This relationship is pictured in Figure 4. We observe that EUA and sCER returns indeed correct the deviations to the long-term equilibrium.

Besides, we observe that the coefficient for the EUA variable (-0.016) is higher than the coefficient for the sCER variable (-0.057), from which we can safely conclude that the EUA price is the leader in the long-term price discovery. Indeed, by combining linearly the short-term variations of EUAs and sCERs, the vector error correction mechanism allows by definition to diminish the fluctuation errors in order to achieve the cointegrating relationship between both variables. Figure 4 shows a reduction in variability in the cointegration relationship in the long-term, as predicted by the vector error correction model. Hence, by looking at the coefficients of the error correction model, we can infer which variable is driving the adjustment towards the long-term relationship in the system.

Finally, we notice the presence of a trend in the cointegrating equation, and the influence of the log-differenced EUA variable lagged one period (the log-differenced sCER variable lagged one period) on the log-differenced sCER variable (the log-differenced EUA variable) at the 1% significance level.

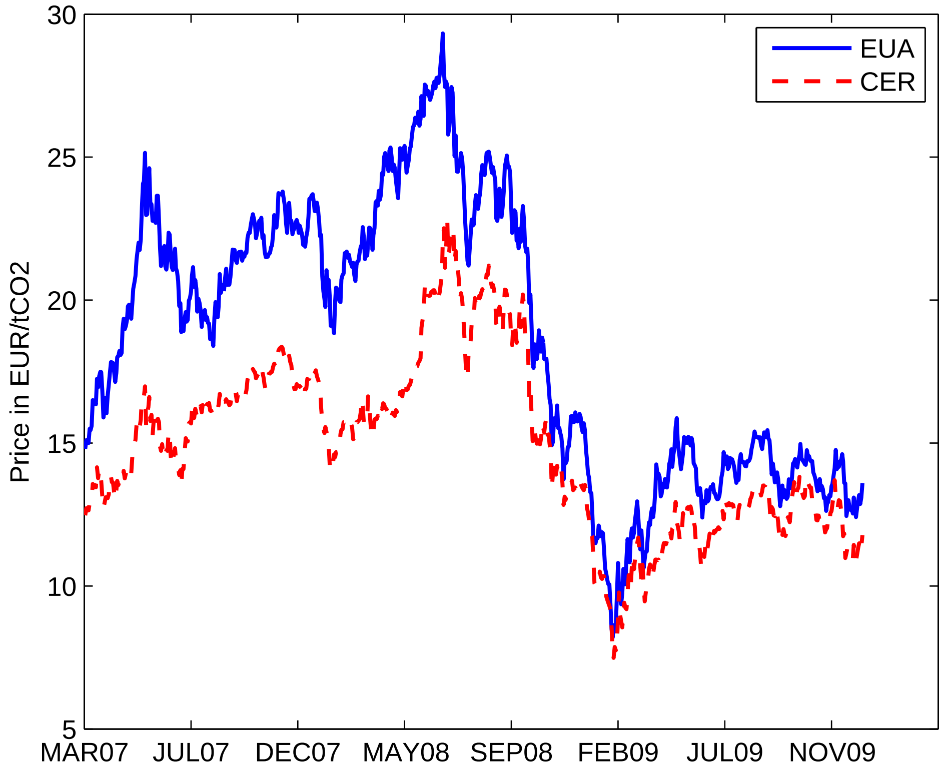
# 6 Conclusion

This paper contributes to the analysis of emissions trading schemes by documenting the statistical relationships between EUAs and sCERs with daily data from March 9, 2007 to January 14, 2010. Testing these inter-relationships appears indeed of particular importance to investors and energy utilities who can 'choose' - up to a fixed limit - between these two assets to exchange emissions allowances and to use them towards compliance within the EU system.

Our results show that there is a clear link between EUAs and sCERs prices: not only do they affect each other at statistically significant levels as shown by the vector autoregressive modeling, but also the transmission of shocks from one price series to the other is quite rapid and significant, as shown by impulse response function analysis.

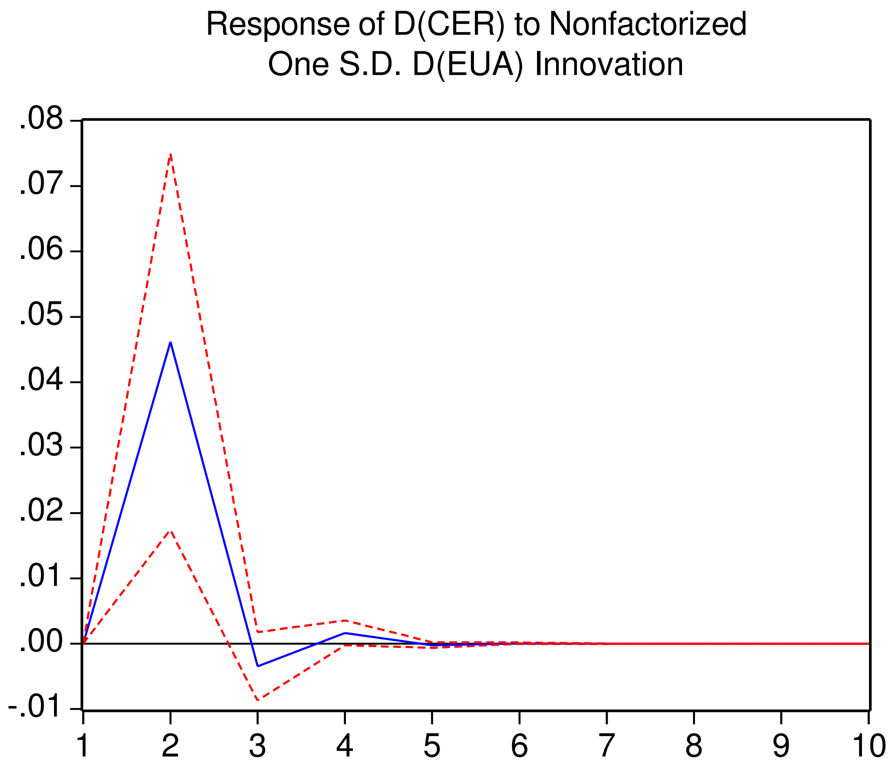
Interestingly, we are able to identify one cointegrating relationship between EUAs and sCERs, which indicates that a long-term relationship exists between these two variables. Finally, our vector error correction models indicates that EUAs tend to lead sCERs in the price discovery process. This result may be explained by the fact that EUAs are the most heavily traded assets when investors, brokers and industrials need to use carbon prices.

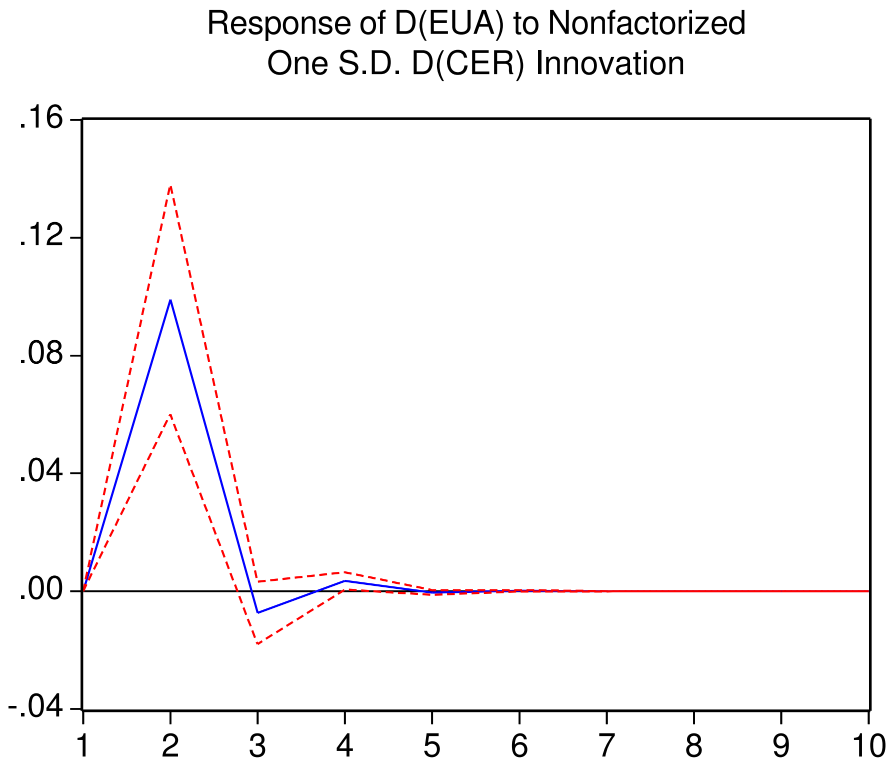
**Figure 1: Time-Series of EUA and sCER Prices.**




Source: ECX, Reuters

**Figure 2: Impulse Response Function Analysis.**




*Note: The solid blue lines represent the Impulse Response Functions, and the red dotted lines represent the confidence intervals.*

**Figure 3: Variance Decomposition Analysis.**

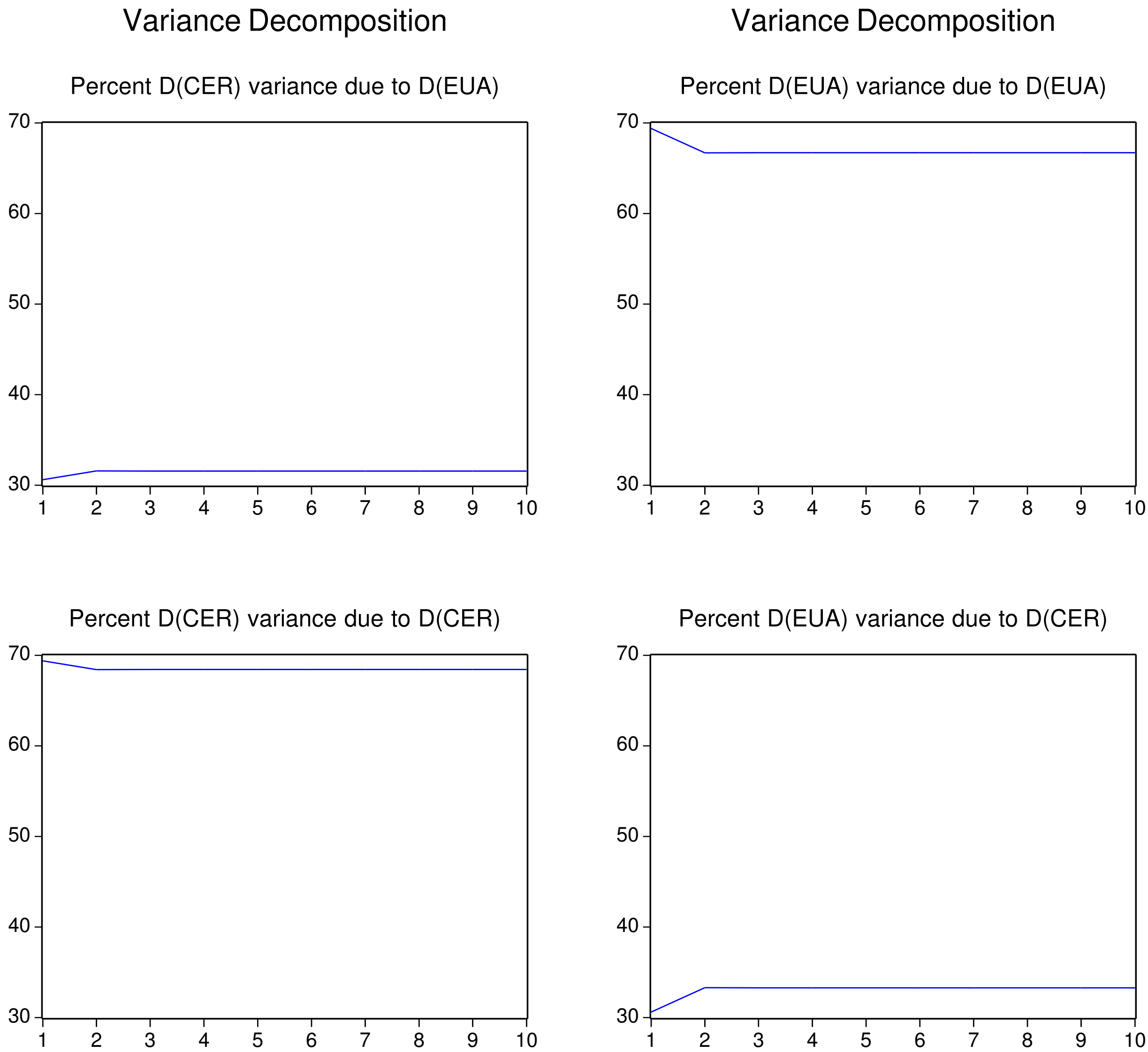


**Figure 4: Cointegrating Relation**.

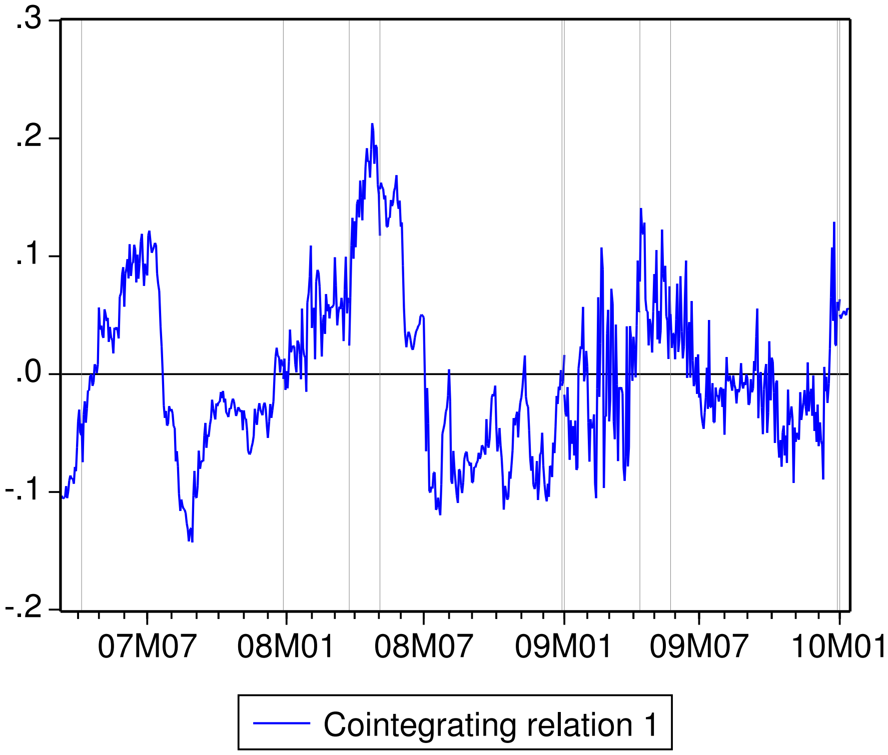


**Table 1: Descriptive Statistics**.

| | EUA | sCER |
|---|---|---|
| Mean | 18.62012 | 14.87575 |
| Median | 19.29000 | 14.73000 |
| Maximum | 29.33000 | 22.85000 |
| Minimum | 8.200000 | 7.484615 |
| Std. Dev. | 4.791531 | 3.034598 |
| Skewness | 0.007144 | 0.238988 |
| Kurtosis | 1.816024 | 2.511116 |
| Jarque-Bera | 42.58584 | 14.19936 |
| Observations | 729 | 729 |

*Note: Std. Dev. refers to Standard Deviation.*

**Table 2: Unit Root Tests for EUA Prices**.

| | t-Statistic | Test critical values |
|---|---|---|
| Augmented Dickey-Fuller test statistic | -24.86266 | -1.941259 |
| Phillips-Perron test statistic | -24.80740 | -1.941259 |

| | LM-Stat. | Asymptotic critical values |
|---|---|---|
| Kwiatkowski-Phillips-Schmidt-Shin test statistic | 0.256730 | 0.463000 |

*Note: For the ADF and PP tests, the null hypothesis is D(EUA) has a unit root (where D(EUA) stands for the first-difference transformation of the EUA price variable). For the ADF test, a lag length of 5 is specified based on the Schwarz Information Criterion. For the PP test, a Bartlett kernel of bandwith 5 is specified using the Newey-West procedure. For both tests, Model 1 (without trend nor intercept) is chosen. Test critical values at the 5% level are based on MacKinnon (1996). For the KPSS, the null hypothesis is D(EUA) is stationary. A Bartlett kernel of bandwith 6 is specified using the Newey-West procedure. Asymptotic critical values at the 5% level are based on KPSS (1992). Model 2 (with intercept) is chosen.*

**Table 3: Unit Root Tests for sCER Prices.**

| | t-Statistic | Test critical values |
|---|---|---|
| Augmented Dickey-Fuller test statistic | -25.80513 | -1.941259 |
| Phillips-Perron test statistic | -25.90880 | -1.941259 |

| | LM-Stat. | Asymptotic critical values |
|---|---|---|
| Kwiatkowski-Phillips-Schmidt-Shin test statistic | 0.166469 | 0.463000 |

*Note: For the ADF and PP tests, the null hypothesis is D(sCER) has a unit root (where D(sCER) stands for the first-difference transformation of the sCER price variable). For the ADF test, a lag length of 0 is specified based on the Schwarz Information Criterion. For the PP test, a Bartlett kernel of bandwith 9 is specified using the Newey-West procedure. For both tests, Model 1 (without trend nor intercept) is chosen. Test critical values at the 5% level are based on MacKinnon (1996). For the KPSS, the null hypothesis is D(sCER) is stationary. A Bartlett kernel of bandwith 9 is specified using the Newey-West procedure. Asymptotic critical values at the 5% level are based on KPSS (1992). Model 2 (with intercept) is chosen.*

**Table 4: Vector Autoregression Estimates**.

| | D(EUA) | D(sCER) |
|---|---|---|
| D(EUA(-1)) | -0.040544 | 0.104888 |
| | (0.04331) | (0.03257) |
| | [-0.93607] | [ 3.22083] |
| | | |
| D(sCER(-1)) | 0.299049 | -0.033974 |
| | (0.05836) | (0.04388) |
| | [ 5.12404] | [-0.77426] |
| | | |
| C | -0.001710 | -0.001097 |
| | (0.01633) | (0.01228) |
| | [-0.10471] | [-0.08935] |
| Schwarz information criterion | | 1.505285 |

*Note: Standard errors in ( ). t-statistics in [ ]. VAR(1) is chosen by minimizing the Schwarz information criterion. D(EUA) and D(sCER) stand for the first-difference transformation of the EUA and sCER price variables, respectively. D(EUA(-1)) and D(sCER(-1)) stand for the first-difference transformation lagged one period of the EUA and sCER price variables, respectively. C stands for the constant. The estimates are presented explicitly under the following form:*

$$D(EUA) = -0.040544 * D(EUA(-1)) + 0.299049 * D(sCER(-1)) - 0.001710$$
$$D(sCER) = 0.104888 * D(EUA(-1)) - 0.033974 * D(sCER(-1)) - 0.001097$$

**Table 5: Pairwise Granger Causality Tests.**

| Lags: 2 | | | |
|---|---|---|---|
| Null Hypothesis: | Obs | F-Statistic | Probability |
| D(sCER) does not Granger Cause D(EUA) | 726 | 16.4668 | 1.0E-07 |
| D(EUA) does not Granger Cause D(sCER) | | 7.99662 | 0.00037 |

| Lags: 4 | | | |
|---|---|---|---|
| Null Hypothesis: | Obs | F-Statistic | Probability |
| D(sCER) does not Granger Cause D(EUA) | 726 | 12.4459 | 8.6E-10 |
| D(EUA) does not Granger Cause D(sCER) | | 7.73055 | 4.2E-06 |

| Lags: 6 | | | |
|---|---|---|---|
| Null Hypothesis: | Obs | F-Statistic | Probability |
| D(sCER) does not Granger Cause D(EUA) | 726 | 9.69815 | 2.8E-10 |
| D(EUA) does not Granger Cause D(sCER) | | 5.83319 | 6.0E-06 |

*Note: D(EUA) and D(sCER) stand for the first-difference transformation of the EUA and sCER price variables, respectively.*

**Table 6: Johansen Cointegration Rank Tests**.

Series: LOG(EUA) LOG(sCER)
Lags interval (in first differences): 1 to 1

| *Trace Test* | | | | |
|---|---|---|---|---|
| Hypothesized No. of CE(s) | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob.** |
| None * | 0.028097 | 28.49151 | 25.87211 | 0.0231 |
| At most 1 | 0.010635 | 7.772792 | 12.51798 | 0.2708 |

| *Maximum Eigenvalue Test* | | | | |
|---|---|---|---|---|
| Hypothesized No. of CE(s) | Eigenvalue | Max-Eigen Statistic | 0.05 Critical Value | Prob.** |
| None * | 0.028097 | 20.71872 | 19.38704 | 0.0319 |
| At most 1 | 0.010635 | 7.772792 | 12.51798 | 0.2708 |

*Note: LOG(EUA) and LOG(sCER) stand for the logarithmic transformation of the EUA and sCER price variables, respectively. CE refers to Cointegrating Equation. Included observations: 727 after adjustments. Trend assumption: Linear deterministic trend. * denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values. Trace test indicates 1 cointegrating eqn(s) at the 0.05 level. Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level.*

**Table 7: Vector Error Correction Estimates.**

| Cointegrating Eq: | CointEq1 | |
|---|---|---|
| LOG(EUA(-1)) | 1.000000 | |
| LOG(sCER(-1)) | -1.152348 | |
| | (0.06573) | |
| | [-17.5320] | |
| Trend | 0.000241 | |
| | (6.5E-05) | |
| | [ 3.71067] | |
| C | 0.109668 | |
| **Error Correction:** | **D(LOG(EUA))** | **D(LOG(sCER))** |
| CointEq1 | -0.015550 | -0.056909 |
| | (0.001382) | (0.01233) |
| | [-11.2681] | [ -4.61425] |
| D(LOG(EUA(-1))) | 0.015105 | 0.230508 |
| | (0.04154) | (0.03673) |
| | [ 0.36365] | [ 6.27514] |
| D(LOG(sCER(-1))) | 0.216236 | -0.026143 |
| | (0.04543) | (0.04017) |
| | [ 4.76006] | [-0.65075] |
| C | -0.000116 | -7.82E-05 |
| | (0.00096) | (0.00086) |
| | [-0.12065] | [-0.09100] |

*Note: LOG(EUA(-1)) and LOG(sCER(-1)) stand for the logarithmic transformation of the EUA and sCER price variables lagged one period, respectively. CointEq stands for Cointegrating Equation. D(LOG(EUA(-1))) and D(LOG(sCER(-1))) stand for the first-difference logarithmic transformation of the EUA and sCER price variables lagged one period, respectively. Trend refers to the deterministic trend. C refers to the constant. Included observations: 728 after adjustments. Standard errors in ( ). t-statistics in [ ].* The model is estimated with intercept and trend in Cointegrating Equation and no trend in the data (Johansen (1995)). The estimates are presented explicitly under the following form:

$$\begin{aligned}
D(LOG(EUA)) = & -0.015550 * (LOG(EUA(-1)) - 1.152348 * LOG(sCER(-1)) + 0.000241 * Trend + 0.109668) \\
& + 0.015105 * D(LOG(EUA(-1))) + 0.216236 * D(LOG(sCER(-1))) - 0.000116 \\
D(LOG(sCER)) = & -0.056909 * (LOG(EUA(-1)) - 1.152348 * LOG(sCER(-1)) + 0.000241 * Trend + 0.109668) \\
& + 0.230508 * D(LOG(EUA(-1))) - 0.026143 * D(LOG(sCER(-1))) - 0.0000782
\end{aligned}$$

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