Impact of International Carbon Credits on the Returns and Volatilities in Regular Emissions Trading Schemes.

Preliminary version. Please do not quote or circulate.

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Abstract
Article 6.4 of the Paris Agreement establishes a new market mechanism, the design of which still needs to be defined. In this context, we conduct an empirical analysis of the impact of international carbon credits on regular emissions trading schemes, in particular on the returns and volatilities. We take advantage of the European experience with accepting Certified Emissions Reductions (CER) for compliance in the second phase of the EU ETS. Our causality analysis uses vector-autoregressive models on the prices of European allowances (EUA) and CER. We also examine the dynamic conditional correlation between the risks of the carbon permits. We find an absence of cointegration between the two price series. This is explained by the difference in their long-term dynamics. The causality analysis shows a unidirectional link from EUA to CER in the short-term: the EUA daily price variations influence the CER returns, but the latter have no impact on the former. 60% of the CER volatility is explained by the EUA volatilty and a shock in the EUA price is always transmitted to the CER price. On the opposite, we find no effect of the CER price variations on the EUA price. The dynamic conditional correlation between the EUA and CER price risks is estimated to be around 0.8, which is comparable to what is observed between commodities that have a high degree of substitutability. In order to ensure the good functioning of these policy instruments, we suggest limiting the volume of international credits that can be issued annually.

Keywords: Emissions trading; European allowances; international credits; causality analysis; dynamic conditional correlation models.

1 Introduction

At the Paris Conference of the Parties (COP) organized within the United Nations Framework Convention on climate change (UNFCCC), Parties agreed upon principles for voluntary market mechanisms. This includes Article 6.2 on internationally transferred mitigation outcomes as well as Article 6.4 which establishes a mechanism that should allow activities to contribute to reductions of emissions in a host Party while being taken into acccount by another Party to fulfill its nationally determined contributions. At the time this paper is written, the exact design of these mechanisms is still being negotiated. No agreement was reached on this point at COP24, deferring the whole to COP25.

In this context, economic analyses of the impacts to expect from such interactions could help designing the new mechanisms. Modeling studies focused on long-term general equilibrium effects have been conducted to assess the effects of sectoral carbon market coupling. Hamdi-Cherif *et al.* (2010) simulated sectoral trading if it were to be used between all industrialized and developing countries. Gavard *et al.* (2011a) examined sectoral trading on a hypothetical US-China carbon scheme coupling using the Emission Prediction and Policy Analysis (EPPA) model. The case of coupling between the EU ETS and carbon markets covering the electricity sectors of China, India, Brazil and Mexico was considered in Gavard *et al.* (2011b). These papers quantify the impacts of such mechanisms on total and sectoral emissions, carbon leakages and financial transfers between the countries involved, over a time period of several decades. They have shown that, in the absence of a limit on the amount of permits that can be traded, such mechanisms would result in carbon price equalisation between the juridictions and might result in a welfare loss for the developing country involved. If a limit is set, the latter effect can be mitigated.

Much of the existing econometric litterature on the price interactions between regular carbon markets and international offsets has focused on the spread between the prices of European allowances (EUA) and Certified Emission Reductions (CER) generated under the Clean Development Mechanism (CDM). Nazifi (2013), Mizrach (2012), Mansanet-Bataller *et al.* (2011) and Chevallier (2010) agree that the price of international credits has been largely influenced by the European carbon market, due to the fact that the latter has been the largest in the world to accept international credits for compliance (Ellerman, Convery, and de Perthuis, 2010; Mansanet-Bataller *et al.*, 2011). The impact of these credits on the regular schemes still needs to be quantified (Trotignon, 2012).

The objective of this paper is to empirically analyze the short-term impacts of international carbon credits on regular carbon markets. In the case of an emissions trading scheme, the supply of permits is fixed, set by a cap that is decided at a political level, while the demand for permits is function of the general economic activity and energy prices and might be influence by the acceptance of international carbon credits. In contrast, for the latter, the supply is influenced by energy prices as well as investment support and the demand is function of the regular ETS.

The European Union Emissions Trading Scheme (EU ETS) provides a good study case: it is the largest carbon market in the world and the largest to have accepted international credits for compliance. Each year, installations covered by the European trading scheme have to surrender carbon allowances in a volume equivalent to the volume of their verified emissions that year. Besides European allowances (EUA), Kyoto Protocol credits are also accepted for compliance under a specific limit. In Phase II of the scheme, this limit was 13% of the amount of EUA issued under the European cap. EUA are issued at the European level, their volume is defined by the European cap and they can only be used for compliance in the European carbon market.[1] CER can be traded worldwide and there is no limit on the amount of CER issued by the CDM board annually.

Our causality analysis employs vector autoregressive models (VAR) on EUA and CER price series during the second phase of the EU ETS. It comprises an impulse response analysis and a variance decomposition. It is complemented by an estimation of the dynamic conditional correlation between the risks embodied in the two price series.

Section 2 describes the data used for this work. Section 3 presents the model used for the causality analysis and the results. Section 4 covers the estimation of the dynamic conditional correlation between EUA and CER price risks. Section 5 concludes.

2 Data

We use CER and EUA time series from Phase II of the EU ETS. Given the fact that the volume of EUA and CER futures contracts is much larger than the volume of spot contracts, we use futures price series. They are constructed by rolling over futures contracts after their expiration date. The source for EUA and CER price series is the Intercontinental Exchange (ICE) database. We use data from February 26^{th}, 2008 to November 12^{th}, 2012 for EUA and data from March 14^{th} 2008 to November 12^{th} 2012 for CER. Natural gas and coal prices[2] are taken from the ICE. We use month-ahead contract price series. Exchange rates from the European Central Bank are used to convert the natural gas price from £ to € and the coal price from $ to €. The Euro Stoxx 50 Index is used to represent the economic activity.[3]

[1] In Phase II of the EU ETS, EUA were given to installations covered by the scheme (grandfathering). Auctions were only introduced at the very end of the year 2012. This latter time period is not included in our analysis.

[2] The coal price we use is the API2 CIF (Cost, Insurance, Freight) with delivery in ARA (Amsterdam, Rotterdam and Antwerp).

[3] There are several reasons for the use of this proxy. First, daily data are available while industrial production is only reported monthly. Daily data on the aggregate European electricity production or consumption are hard to find. The national level data that are available present some seasonality and do not well reflect the changes in the economic activity. Finally, other authors also use this proxy to analyse the European trading scheme. That is, for example, the case in Bredin and Muckley (2011), and Creti et al. (2012).

Figure 1 presents the EUA and CER futures price series. As identified by the Clemente Montanès and Reyes test in Gavard and Kirat (2018) and reported in the appendix, the carbon price series present two breaks in level. The first one is related to the economic and financial crisis in 2008 while the second one corresponds to a recession in Europe in the third trimester of 2011. In addition, for the international credits, we observe a break in trend from November 2011 onwards. As early as January 2009, the European Commission announced that there would be restrictions on the type of credits accepted for compliance in the European carbon market, but the list of credit types that would be recognized or not was only published in January 2011. Visually the break in trend seems to start then, but the test detects the break only at the end of 2011. Two additional explanations remain. On the one hand, there was a limit on the volume of credits that each installation covered by the scheme could use for compliance. As installations reached their respective limits, the demand for these carbon permits gradually decreased. On the other hand, Gavard and Kirat (2018) suggest that increasing global fossil energy prices might have had an impact of the development of CDM projects and, as a consequence, on the supply of credits to the market. This supply effect in addition to the reduction in demand would explain the drop in the CER price in 2012.

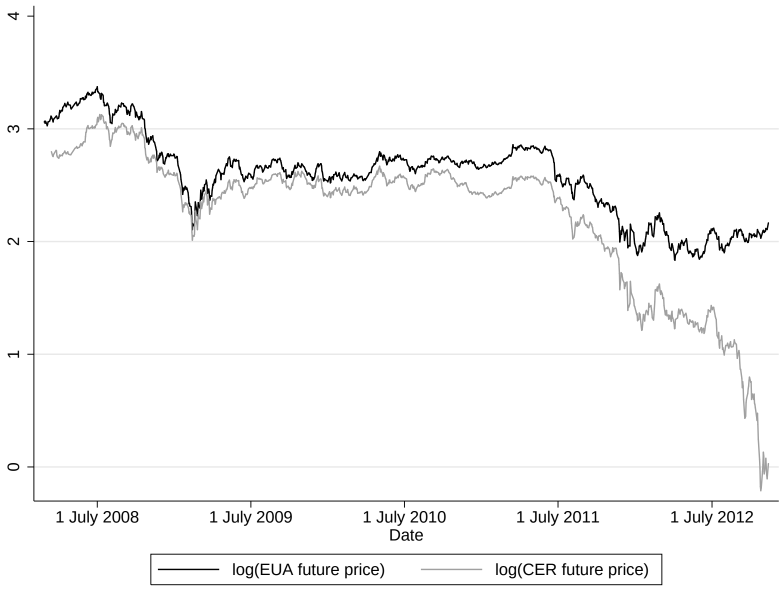
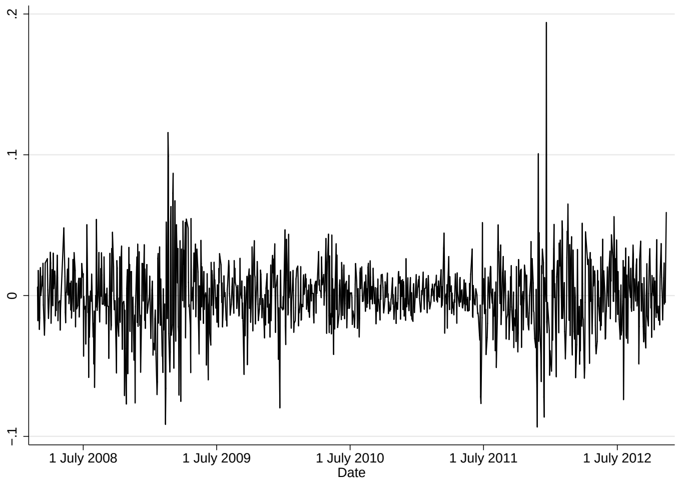


Figure 1: Logarithmic EUA and CER futures prices.

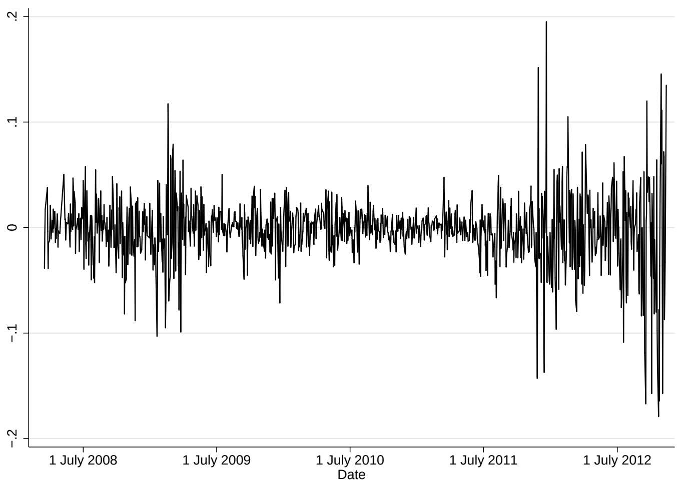
Figure 2 shows the daily variations of the EUA and CER futures price series. The variations for the other price series are in appendix, as well as the summary statistics of the returns are in the appendix (see Table 4). As described in Gavard and Kirat (2018), the EUA and CER returns display patterns of volatility clustering. This is consistent with previous observations reported in the literature, e.g. by Medina and Pardo (2012) or Paolella and Taschini (2008). We note that the volatility is higher after each of the two breaks described above. The economic recessions at the end of 2008 and 2011 induced uncertainty and a higher carbon price volatility.

3 Causality analysis

In this section, we perform the causality analysis between the EUA and CER price series using vector autoregressive (VAR) models. Given the impact of energy prices and the economic activity on the



(a)



(b)

Figure 2: (a) EUA and (b) CER price variations.

carbon price, we conducted this analysis with three different specifications, one with the energy prices and the economic activity as endogenous variables, one with them as exogenous variables, and one without them. We found very close results for the three specifications. Here, we report the results for the simplest one, that is the model including the EUA and CER prices only.

Before conducting the estimation with the VAR model, we test the existence of a long-term relationship between the two price series. Several authors have already noticed the absence of a cointegration relationship between EUA and CER price series: Nazifi (2013) for the time period from March 2008 to May 2009, Mizrach (2012) for the time period from June 2007 to April 2010.[4] The observation of the EUA and CER prices over time (Figure 1) already suggests the absence of cointegration. Even if EUA and CER prices have common drivers and might influence one another, the Engle Granger test, which takes account of breaks in the series, confirms the absence of a long-term relationship between the EUA and CER prices on the time period from February 2008 to November 2011. The results reported in Table 1 show that we cannot reject the null hypothesis of no cointegration. We explain this by the fact that even if EUA and CER prices are driven by similar factors, their long-term dynamics are different (Gavard and Kirat, 2018). The EUA price is demand-driven; its supply is set by a cap; the price variation are explained by the change in demand for carbon permits. On the contrary, for the CER price, the long-term dynamics seem to be influenced by a potential supply effect related to investments in CDM projects.

Table 1: Results of the Engle-Granger cointegration test.

Null hypothesis	Test statistic	1% Critical value	5% Critical value
P^{CER} and P^{EUA} are not cointegrated	3.801	-3.906	-3.341

Note: the null hypothesis of no cointegration is rejected if the test statistic is below the critical value. Critical values are taken from MacKinnon (1990, 2010).

The causality relationship between the EUA and CER prices is tested with the following VAR model with two lags.[5]

$$\begin{cases} \Delta P_t^{EUA} = \alpha_1 + \beta_1 \Delta P_{t-1}^{EUA} + \gamma_1 \Delta P_{t-2}^{EUA} + \delta_1 \Delta P_{t-1}^{CER} + \lambda_1 \Delta P_{t-2}^{CER} + \varepsilon_{1t} \\ \\ \Delta P_t^{CER} = \alpha_2 + \beta_2 \Delta P_{t-1}^{EUA} + \gamma_2 \Delta P_{t-2}^{EUA} + \delta_2 \Delta P_{t-1}^{CER} + \lambda_2 \Delta P_{t-2}^{CER} + \varepsilon_{2t} \end{cases}$$

where ΔP_t^{EUA} and ΔP_t^{CER} are respectively the price variations of EUA and CER in period t, and ε_{1t} and ε_{2t} the error terms corresponding to each relationship.

The results of the Granger causality tests are presented in Table 2. We find that short-term variations in the EUA price cause variations in the CER price, but that the opposite is not true. The null hypothesis that variations in the price of EUA does not cause variations in the price of CER is rejected, while the hypothesis that variations in the price of CER does not cause variations in the price of EUA is not.

In order to perform an impulse-response analysis, we use the Cholesky decomposition to orthogonalize ε_1 and ε_2. The estimation of the VAR model is used to simulate a shock on the EUA price and look at the impact on the CER price, and, symetrically, simulate a shock on the CER price and examine the impact on the EUA price. Figures 3 and 4 show the results of the analysis. We observe that a shock on the EUA price is immediately transmitted to the CER price. This effect is amortized in two days and it disappears after four days. On the contrary, a shock on the CER price has no significant impact on the EUA price.

[4] Mansanet-Bataller *et al.* (2011) and Chevallier (2010) find some cointegration between EUA and CER prices, but Mizrah (2012) suggests that this is due to the fact that they use the Reuters index for the CER data and that this index averages prices from different expiries.

[5] The number of lags is chosen according to the Akaike and Hannan-Quinn information criteria.

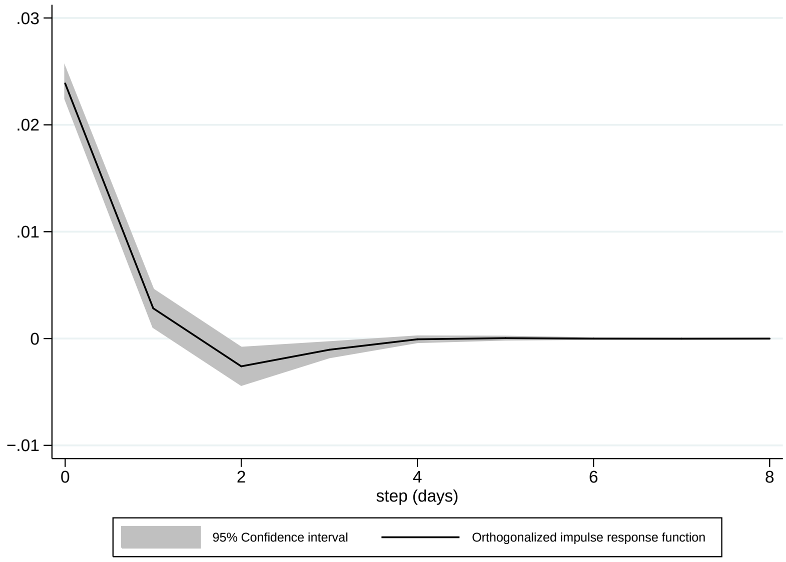


Figure 3: Response in the variation of the logarithmic CER price to an impulse in the variation of the logarithmic EUA price.

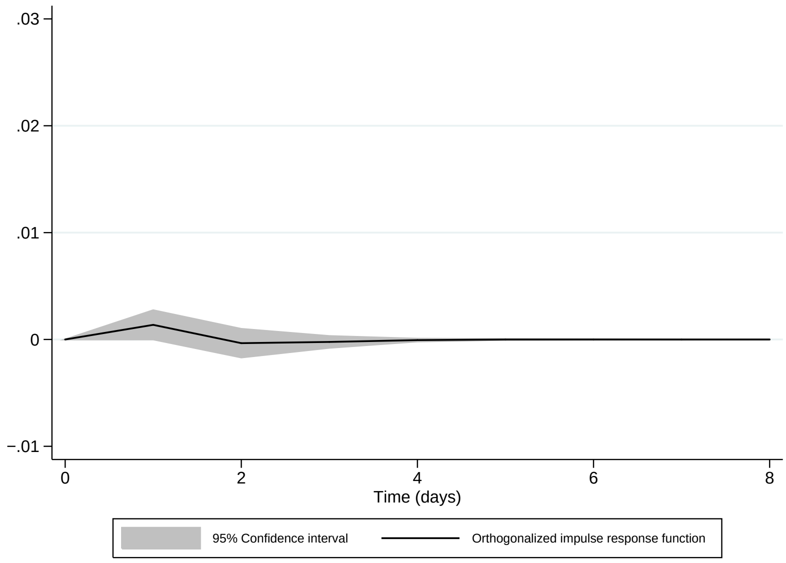


Figure 4: Response in the variation of the logarithmic CER price to an impulse in the variation of the logarithmic EUA price

Table 2: Results of the Granger causality tests.

Null hypothesis	LR statistic	Granger causality test (Prob $>\chi^2$)
ΔP^{EUA} does not Granger cause ΔP^{CER}	17.171	0.000***
ΔP^{CER} does not Granger cause ΔP^{EUA}	4.5805	0.101

Note: *** and ** respectively refer to rejection of the null hypothesis at the 1% and 5% significance levels.

We also proceed to the variance decomposition of the EUA and CER prices. This allows to assess the share of the CER price volatility that is explained by the EUA price volatility and, symetrically, the share of the EUA price volatility that is explained by the CER price volatility. The results are presented in Table 3. We find that the EUA price volatility explains 60% of the CER price volatility, while the CER price volatility has no impact on the EUA price volatility.

Table 3: Variance decomposition of the forecasted errors.

	Variance decomposition of ΔP^{EUA}		Variance decomposition of ΔP^{CER}	
Period	ΔP^{EUA}	ΔP^{CER}	ΔP^{EUA}	ΔP^{CER}
1	100%	0%	61.96%	38.04%
2	99.68%	0.32%	60.31%	39.69%
3	99.66%	0.34%	60.39%	39.61%
4	99.65%	0.35%	60.42%	39.58%
5	99.65%	0.35%	60.42%	39.58%
6	99.65%	0.35%	60.42%	39.58%
7	99.65%	0.35%	60.42%	39.58%
8	99.65%	0.35%	60.42%	39.58%

All these results show a unidirectional influence of the EUA on the CER. There are three reasons for this. First, the EUA market is much larger than the CER market: the number of EUA issued annually (more than 2 billion in 2013) is in the same order of magnitude as the cumulative number of CER generated (1.9 billion indicated on the CDM pipeline[6] on January 29^{th}, 2019). Second, the demand for CER has come mainly from the EU ETS. Third, the volume of CER that could be used for compliance in the EU ETS was limited to 13% of the overall cap in the second phase of the scheme.

4 Estimation of the correlation between the carbon permits risks

Complementary to the causality analysis performed above, we estimate the correlation between the EUA and CER price volatilities. We consider the interdependence between the risks embedded in the EUA and CER prices and we model the conditional volatility of these carbon permit price variations in a manner that allows for the existence of a time varying conditional correlation matrix. We specify the following model with Dynamic Conditional Correlation (Engle, 2002; Engle and Sheppard, 2001) $\mathrm{DCC}_E(1,1)$ errors:

[6] Detailed information on CDM projects is provided by the Centre on Energy, Climate and Sustainable Development: UNEP DTU CDM/JI Pipeline Analysis and Database (cdmpipeline.org).

$$
\begin{cases}
\begin{cases}
\Delta P_t^{EUA} = \alpha_1 + \beta_1 \Delta P_{t-1}^{EUA} + \gamma_1 \Delta P_{t-2}^{EUA} + \delta_1 \Delta P_{t-1}^{CER} + \lambda_1 \Delta P_{t-2}^{CER} + \varepsilon_{1t} \\
\\
\Delta P_t^{CER} = \alpha_2 + \beta_2 \Delta P_{t-1}^{EUA} + \gamma_2 \Delta P_{t-2}^{EUA} + \delta_2 \Delta P_{t-1}^{CER} + \lambda_2 \Delta P_{t-2}^{CER} + \varepsilon_{2t}
\end{cases} \\
\\
(\varepsilon_{1t}, \varepsilon_{2t})^T \mid \Omega_t \rightsquigarrow N(0, H_t) \ where \ \Omega_t \ is \ the \ available \ information \ at \ time \ t
\end{cases}
\tag{1}
$$

The $DCC_E(1,1)$ model is defined as:

$$
\begin{cases}
H_t = D_t R_t D_t \\
D_t = diag(\sqrt{h_{11t}}, \sqrt{h_{22t}}) \\
R_t = (diag\ Q_t)^{1/2}\ Q_t\ (diag\ Q_t)^{-1/2}
\end{cases}
$$

where the 2×2 symmetric positive definite matrix Q_t is given by:

$$
Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 u_{t-1} u_{t-1}^T + \theta_2 Q_{t-1}
$$

Here u is the matrix of standardized residuals, $\overline{Q}$ is the 2×2 unconditional variance matrix of u_t, and θ_1 and θ_2 are non-negative parameters satisfying $\theta_1 + \theta_2 < 1$. The $DCC(1,1)$ model can be estimated either in one single step or in two steps.[7] In the latter case, the conditional-mean equations and the conditional variances of EUA and CER price variations are first estimated using a $GARCH(1,1)$ specification corresponding to the VAR model. The standardized residuals are then used to model the correlation in an autoregressive manner to obtain the time-varying conditional correlation matrix. The conditional variance-covariance matrix H_t is the product of the diagonal matrix of the conditional standard deviation D_t with the conditional correlation matrix R_t and the matrix D_t. The $R_t = \begin{pmatrix} 1 & \rho_{12t} \\ \rho_{21t} & 1 \end{pmatrix}$ matrix reflects the instantaneous conditional correlation between EUA and CER price variations. Figures 5 and 6 respectively represent the EUA and CER price volatilities and the dynamic conditional correlation between them.

CER and EUA volatilities are very close until November 2011. Afterwards, the CER price volatility is much higher, while its return remains lower than the EUA return. November 2011 also coincides with the second break in the CER price series identified in section 2. This higher volatility reflects an increased uncertainty, which may be related to the risk that the limit of offsets accepted for compliance in the EU ETS is reached. This would be consistent with the indication by Ellerman *et al.* (2010) that the price difference between EUA and CER is related to the risk of the CER not being accepted in the European carbon market and to a delivery risk, mainly the risk of CER futures contracts not being backed by already issued CER.

The estimation of the dynamic conditional correlation between the volatilities of the EUA and CER prices shows it is positive and high. It varies between 0.41 and 0.92. Its mean is 0.81. For comparison, Engle (2002) finds that the dynamic conditional correlation between the Dow Jones Industrial Average and the NASDAQ Composite varies between 0.4 and 0.9 in the time period 1990-2000. Gupta and West (2013) observe that the DCC between the prices of various types of coal imported to India is close to 1, and Marzo and Zagaglia (2008) show that there is a DCC close to 0.8 between the prices of crude oil and heating oil. The DCC observed here between the prices of CER and EUA is high compared to what is seen for traditional financial products, it is rather in line with the DCC observed between the prices of commodities that have some degree of substitutability.

[7] See the Appendix for more details regarding the model estimation.

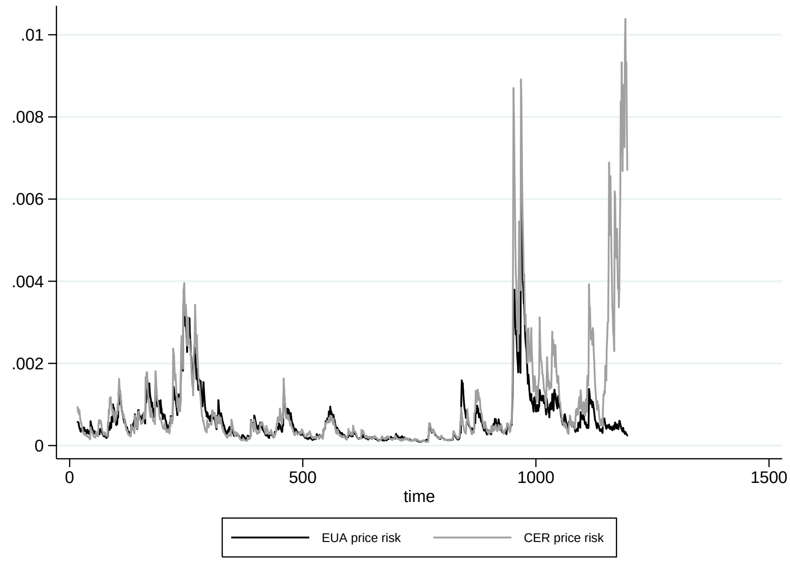


Figure 5: EUA and CER price risks.

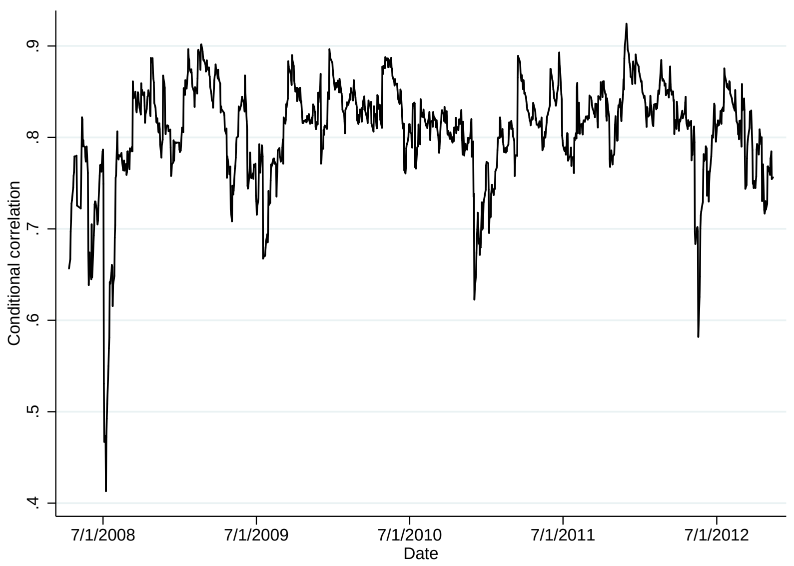


Figure 6: Dynamic conditional correlation between the EUA and CER prices.
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5 Conclusion

In the framework of the UNFCCC, Article 6.4 of the Paris Agreement establishes a mechanism that allows reductions of emissions in a host Party to be taken into account by another Party to fulfill its Nationally Determined Contributions. The institutional form this mechanism will take still needs to be designed as the definition of the corresponding modalities and procedures has been postponed from COP24 to COP25.

In this context, this paper conducts an empirical analysis that aims to shed light on the impact of international credits on regular emissions trading schemes, in particular on the returns and volatilities in the latter. It takes advantage of the European experience with accepting Certified Emissions Reductions for compliance in the second phase of the EU-ETS. The causality analysis that is presented employs vector-autoregressive models of the prices of EUA and CER. It allows quantifying the impact of each carbon permit type on the other one and decomposing the corresponding volatilities. We finally estimate the dynamic conditional correlation between the risks of the carbon permits.

We find no cointegration relationship between the EUA and CER prices. This is consistent with previous literature results, including the observation by Gavard and Kirat (2018) that EUA and CER price series are driven by different long-term dynamics. While the volume of EUA issued annually is set by a cap and the price is hence demand-driven, the CER price might be influenced by a supply-side effect related to investment in CDM projects. The restrictions on the use of CER credits in the following time periods of the European scheme as well as the uncertainty regarding the question whether the limit of CER accepted in the EU ETS would be reached are also likely to have contributed to the downward trend in the CER price in 2012.

The VAR analysis shows a unidirectional causality link between EUA and CER in the short-term: the EUA daily price variations influence the CER returns, but the latter have no impact on the former. 60% of the CER price volatility is explained by the EUA volatility, while the CER price volatility has no effect on the EUA. Shocks in the EUA price are transmitted to the CER price, but the opposite is not true. The direction of this causal relationship from the EUA to the CER price can be explained by three factors. First, there is a major difference in market size between the two types of permits: the number of EUA issued for a single year is in the same order of magnitude as the cumulative number of credits that have been generated since the CDM started. Second, the main source of demand for CER has been the EU ETS. Third, the volume of CER that could be used for compliance in the second phase of the European carbon market was limited to 13% of the volume of EUA.

We observe that the EUA and CER volatilities are very close until November 2011. Afterwards, the CER volatility is much higher and the CER price falls. This can be related to the uncertainty mentioned above as well as the decision made at the the 17^{th} COP in Durban to reform the CDM. We find that the dynamic conditional correlation between the price risks of CER and EUA is around 0.8, which is higher than what is seen for traditional financial products. It is rather close to the DCC observed between the prices of commodities that have some degree of substitutability.

In terms of policy implications, the absence of an influence of the CER price on the short-term variations in the EU carbon market is rather positive. In this regard, setting a limit on the volume of international credits that can be accepted in a regular ETS makes sense to ensure the effective functioning of the latter as a policy instrument. On the other hand, such limits and restrictions might cause low prices and high volatility of international carbon credits. This may undermine the interest of investors in using such credits and, as a consequence, reduce the potential support for low-carbon projects in developing countries. One idea that would be worth considering is to set a global limit on the volume of international credits generated annually. Together with strict rules for issuing such permits, this could help to maintain a higher price for these international credits and reduce the risk of issuing more credits than the amount that can be accepted in the regular trading schemes.

Acknowledgments

The authors wish to thank K. Schubert, J. Chevallier, H.D. Jacoby, K. Millock, P. Quirion, and L. Ragot for their useful comments on this research. The opinions expressed in the paper are those of the authors. Any remaining shortcomings are the authors' responsibility.

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Appendices

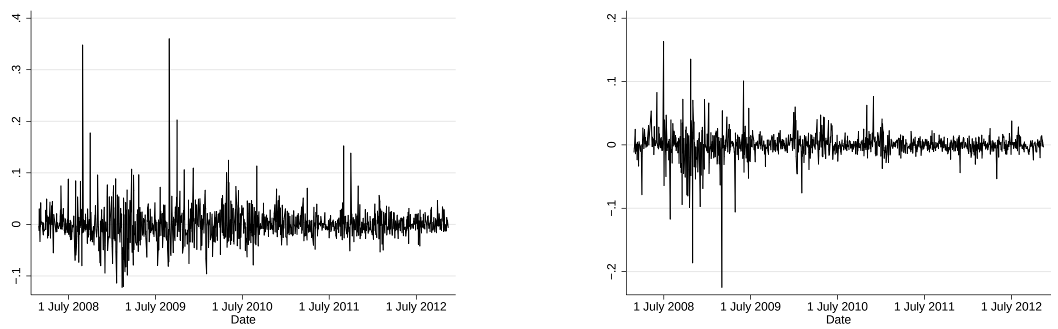
A. Data description and tests

Descriptive statistics

Table 4: Descriptive statistics of the daily variations of the logarithmic price series

Variable	Nb. of Obs.	Mean	St. Dev.	Min.	Max.
EUA	1195	-0.00075	0.024	-0.093	0.193
CER	1182	-0.00234	0.031	-0.179	0.195
Gas	1195	0.0001495	0.03297	-0.1220	0.3600
Coal	1195	-0.0002768	0.02031	-0.2248	0.1631
Eurex	1195	-0.0003692	0.01823	-0.08208	0.1044

Returns of the energy prices

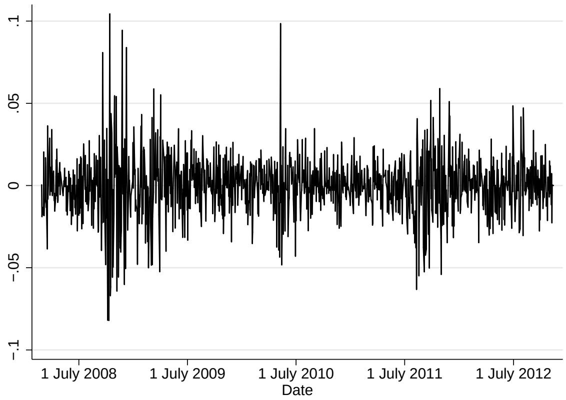


(a) Gas price variations

(b) Coal price variations

Figure 7: Energy price returns (first difference of logarithmic prices)

Return of the economic activity



(a)

Figure 8: Return of the Euro Stoxx 50 Index

Clemente Montañès and Reyes test

In the Clemente Montañès and Reyes test, break dates are endogenous. It includes two test procedures. The Additive Outlier (AO) procedure applies a filter to detrend the series before performing the unit root test. It captures sudden changes in the series. The Innovational Outlier (IO) procedure detrends and performs the unit root test at the same time. It captures incremental changes in the mean of the series. The results of the test on EUA and CER price series are summarized in Table 5. The two procedures show that the EUA and CER futures price series presents two break dates. They are slightly different depending on the test procedure but they are very close, which reveals the robustness of the results. EUA and CER futures price series present breaks in level in November 2008 and November 2011. For the CER series, there is an additional break in trend in November 2011.

Table 5: Results of the Clemente Montañès and Reyes test on EUA et CER permit prices (in logarithms).

	EUA future price				CER future price			
Test procedure	IO		AO		IO		AO	
Series	Level	Variation	Level	Variation	Level	Variation	Level	Variation
DU_1	-0.016	0.002	-0.546	0.0036	-0.006	-0.005	-0.471	-0.021
	(-4.67)	(1.47)	(-49.46)	(1.955)	(-1.90)	(-0.669)	(-22.90)	(-2.79)
	{0.000}	{0.141}	{0.000}	{0.052	{0.058}	{0.504}	{0.000}	{0.005}
DU_2	-0.016	0.0005	-0.606	0.0011	-0.006	-0.0003	-1.298	0.016
	(-4.82)	(0.287)	(-63.43)	(0.608)	(-1.39)	(-0.038)	(-72.74)	(2.08)
	{0.000}	{0.774}	{0.000}	{0.543}	{0.163}	{0.970}	{0.000}	{0.037}
$\rho-1$	-0.028	0.925	-0.034	-0.895	-0.005	-0.899	-0.014	-0.904
	(-5.36)	(-25.43)	(-4.67)	(-10.66)	(-1.427)	(-24.34)	(-2.473)	(-10.12)
	[-5.49]	[-5.49]	[-5.49]	[-5.49]	[-5.49]	[-5.49]	[-5.49]	[-5.49]
Conclusion	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$
Significant	13/10/08		03/11/08				21/11/08	23/11/11
dates of breaks	15/09/11		28/11/11				28/11/11	16/12/11

Note: The values in () and [] are respectively the t-statistics and the critical values at the 5% significance level tabulated by Clemente Montañès and Reyes. Values in {} are p-values.The null hypothesis of the unit root test is rejected when the t-statistic is smaller than the critical value.

B. Two-step estimation of DCC$_E$ models.

The estimation of the parameters of multivariate models is based on the maximum-likelihood method. With Gaussian residuals, the likelihood function is:

$$L_T = \sum_{t=1}^{T} \log f(y_t \mid \theta, \eta, I_{t-1})$$

Here $f(y_t \mid \theta, \eta, I_{t-1}) = |H_t|^{-\frac{1}{2}} g(H_t^{-\frac{1}{2}}(y_t - \mu_t))$, the density function of y_t given the parameter vector θ and η. We assume that $(y_t - \mu_t) \rightsquigarrow N(0, I_N)$. Thus, the log-likelihood function is:

$$L_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left[\log|H_t| + (y_t - \mu_t)' H_t^{-1}(y_t - \mu_t)\right]$$

The Gaussian likelihood provides a consistent quasi-likelihood estimator, even if the true density is not Gaussian. In the case of a DCC model the log-likelihood consists of two parts. The first part depends on the volatility parameters and the second one on the parameters of the conditional correlations given the volatility parameters. With $H_t = D_t R_t D_t$, we obtain:

$$L_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left[\log|D_t R_t D_t| + u_t' R_t^{-1} u_t\right]$$

where $u_t = D_t^{-1}(y_t - \mu_t)$ and $u_t' R_t^{-1} u_t = (y_t - \mu_t)' D_t^{-1} R_t^{-1} D_t^{-1}(y_t - \mu_t)$. With this notation, the log-likelihood is:

$$L_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left[\log|D_t R_t D_t| + u_t' R_t^{-1} u_t\right]$$

$$L_T(\theta) = \underbrace{-\frac{1}{2}\sum_{t=1}^{T}[2\log|D_t| + u_t' u_t]}_{Q1L_T(\theta_1^*)} \underbrace{-\frac{1}{2}\sum_{t=1}^{T}\left[\log|R_t| + u_t' R_t^{-1} u_t - u_t' u_t\right]}_{Q2L_T(\theta_1^*, \theta_2^*)}$$

where θ_1^* represent the parameters of the conditional variance D_t and θ_2^* those of the conditional correlation R_t. The log-likelihood function can then be written as follows:

$$L_T(\theta) = Q1L_T(\theta_1^*) + Q2L_T(\theta_1^*, \theta_2^*)$$

The coefficients (θ_1^*, θ_2^*) are estimated in two stages. In the first stage, we estimate $\theta_1^* = \arg\max Q1L_T(\theta_1^*)$ and, in the second one, we estimate $\theta_2^* = \arg\max Q2L_T(\theta_1^*, \theta_2^*)$.

C. Estimation results of the DCC$_E$ model.

Table 6: Estimation results of the DCC model.

	Variance equation			
	CER price variations		EUA price variations	
$ARCH$	0.167***	(0.000)	0.144***	(0.000)
$GARCH$	0.832***	(0.000)	0.855***	(0.000)
$cons$	0.000***	(0.000)	0.000***	(0.000)
	Correlation parameters			
θ_1	0.054***	(0.000)		
θ_2	0.879***	(0.000)		

Note: P-values are in (); *, ** and *** respectively refer to the 10%, 5% and 1% significance levels of the estimated coefficients.