CO_2 emission allowances and their interacion with economic and energy factors in the European Union

Los derechos de emisión de CO_2 y su interacción con los factores económicos y energéticos en la Unión Europea

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Originales: Recepción: 28/02/2020 - Aceptación: 21/12/2020

Abstract

Analysis of emission allowances prices has important environmental and political connotations. This article aimed to identifying the possible variables that may influence their behaviour and studied their relationship with fundamental factors: energy (brent petroleum, gas, coal) and economy (industrial production index, baltic dry index, purchasing managers index). With the objective of analyzing possible mutual interactions, Multivariate VAR or Error Correction Models (VECM), were applied. The information analysed derived from different sources (World Bank, Sendeco2 and various financial websites). The results obtained showed, not only the influence of past prices on the emission allowances actual price, but also the interaction with energetic and economic variables.

Keywords

VAR & VECM model • cointegration • allowances emission • environment • fundamental factors

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Resumen

El análisis del precio de los derechos de emisión resulta de gran interés por sus connotaciones medioambientales y políticas. Por ello, este artículo se centra en identificar las posibles variables que pueden influir en su comportamiento y estudiar su relación con factores fundamentales: energéticos (petróleo brent, gas, carbón) y económicos (índice de producción industrial, índice báltico seco, índice de gestión de compras). La técnica multivariante aplicada corresponde a modelos VAR o en su caso de corrección de errores (VECM). La información utilizada procede de diversas fuentes (Banco Mundial, Sendeco2 y de diversas web de carácter financiero). Los resultados obtenidos manifiestan no solo la influencia de los precios pasados en el precio de los derechos de emisión sino también la interacción de las variables energéticas y económicas sobre aquellos.

Palabras clave

modelo VAR/VECM • cointegración • derechos de emisión • medioambiente • factores fundamentales

Introduction

Climate change has become one of the most complex challenges of this century. No country is exempt, nor can face this global problem alone. As a current priority for all societies, international cooperation needs to address this environmental challenge with coordinated policies aiming at stabilizing or reducing greenhouse gas levels.

In this context, economic growth and reducing emissions constitute priority objectives. Making them compatible is essential in order to sustainably grow while fighting against climate change (17, 18, 20). For many years now, the fact that economic growth has increased greenhouse gas emissions causing intensified energy absorptions and aggravating the greenhouse effect, has produced widespread awareness.

Concerns regarding increasing greenhouse gas emissions have led to certain international consensus about fighting climate change. A series of legal regulations intended to deal with this problem, have also been issued. Thus, two international treaties were drafted: the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol.

In 1994, the Framework Convention on Climate Change (United Nations, 1992) came into force in numerous countries. In the case of the EU, it was ratified by 94/69/EC: Council Decision, 15 December 1993. This Convention recognized an increase in greenhouse gas concentration both due to human causes and natural factors (Article 1). In view of this, the Convention sought to achieve stabilization of atmospheric CO_2 while pursuing sustainable economic development. However, this Framework Convention neither imposed restrictions on the emission of greenhouse gases, nor established mechanisms for their reduction.

To extend that treaty and proceed in the fight against climate change, in 1997 the famous 'Kyoto Protocol' established emission limits for developed countries. Subsequently, meetings called "Conference of the Parties" (COP) aimed to develop the actions to be consequently followed. Among the 25 conferences held to date, in the 'Paris Agreement' adopted in 2015, countries promised to limit global warming to 1.5 °C above pre-industrial levels.

In this context, reduced emissions have constituted a global and climatic priority. However, the way to achieve this goal, has been neglected. A number of instruments, known as flexibility mechanisms, were introduced with the intention of upholding the commitments undertaken by the Parties. Thus, these "Joint Implementation" mechanisms regulated the investment resulting from projects aiming at limiting anthropogenic emissions in industrialized countries. Another mechanism was "Clean Development", which consisted of an industrialized country investing on a developing country. Another way of upholding the commitments in the Protocol was the possibility of negotiating emission allowances. This is currently the most widely used procedure and has led to the creation of a financial market for these assets (European Emission Allowances, EUA).

With focus on economic theory, some researchers consider that Greenhouse Gas emissions are negative externalities associated with climate change, considered a "public bad" complying with the conditions of non-rivalry and non-exclusion (16, 21). Furthermore, given this condition of “public bad”, it turns evident that a solution to the problem requires global commitment (5). Therefore, estimating a proper carbon price turns indispensable for an emissions reduction strategy (19). Economic literature describes the calculation of social prices and the CO_2 shadow price. Market price, social cost of carbon and marginal cost of reducing emissions were identified as evaluation methods (4). Additionally, carbon pricing can be implemented through carbon credits price as a proxy variable of society’s willingness to pay for reducing GHG emissions. However, this does not seem to reflect the true social value (5).

Considering this background, this article investigated the relationship between emission allowances pricing and energy and economic variables. This interrelation is considered a starting hypothesis, to be contrasted through its analysis. Consequently, the objective of this work focused on modelling emission allowances prices along with energy and economic factors, during the 2008-2019 period. This analysis intended to identify certain variables that may influence the emission allowances prices, and if the latter could affect the former. To this end, their relationships were studied through autoregressive vector models (VAR) and error correction (VECM). These models are useful when evidence of a certain temporal relationship between variables, is available (12, 13, 22).

Material and methods

Studies on emission allowances have focused on two different approaches, one regulatory and another related to the analysis of emission allowances prices. When considering this analysis, and given the existing knowledge on the market and its possible interrelations, to reference both approaches seems necessary.

Regulatory framework of emission allowances

In relation to the regulatory context, a wide range of international regulations have been issued. In Europe, Decision 2002/358/EC, ratified the Kyoto Protocol, and the EU committed to reduce its greenhouse gas emissions, however, with a different distribution among the member states.

In order to meet the objective set by the Kyoto Protocol, the EU issued Directive 2003/87/EC, amended by Directive 2004/101/EC and Directive 2009/29/EC, among others, establishing a regime for the EU Emission Trading Systems (EU-ETS). These directives constituted complementary instruments for cost reduction and efficiency improvement of emissions. This trading scheme established a market mechanism called “cap and trade”, setting a total limit on annual greenhouse gas emissions and a trading system for these allowances. It also established allowance equivalence, an instrument which allowed emitting a ton of carbon dioxide equivalent, within a certain period of time. Furthermore, this allowance was negotiable and transferable.

Different phases for developing this emission allowances trading regime, were established. Pilot phase I, lasted three years (2005-2007). The EU Emission Trading System (EU-ETS) was launched in January 2005 and each State defined its own emission ceiling with a decentralized allowance apportionment structure. Overall, allowance allocation was free of charge while facilities’ historical activity constituted the reference point determining the quantity of allowances. This led to emission overestimation and resulted in market allowances excess.

Phase II lasted five years (2008-2012) and free allowance allocation was the chosen procedure meeting undertaken commitments undertaken by each Member State. Additionally, a series of instruments relaxing these commitments, were introduced: The “Banking” instrument allowed acquired emission rights to be used in a subsequent period, while “borrowing”, meant that emissions and the corresponding emission allowances from a preceding period, could be fulfilled with allowances issued in subsequent periods.

Phase III (2013-2020) introduced big changes and carried out an important revision of the EU-ETS regulated by Directive 2003/87/EC, intended to promote the efficient reduction of greenhouse gas emission. Thus, the EU issued Directive 2009/29/EC, which partially amended Directive 2003/87/EC improving and expanding the EU-ETS, and committing to limit global greenhouse gas emission on at least 20% of 1990 levels, by 2020. This set an emission ceiling in Europe, with a 1.74% annual linear decrease of allowances, up to 2020.

This phase also eliminated free allotment of emission allowances for power generators. In the industry, free allotment is temporary, and based on EU benchmarks rather than on facilities' historic indicators. This temporary allotment is to be gradually reduced over time, going from an initial 80% in 2013 to 30% in 2020 and 0% in 2027. However, exceptions are established for those facilities exposed to "risks of carbon leakage", getting 100% of their allowance free of charge (relocation of industries in countries with no legislation equivalent to EU-ETS).

Another relevant element of Directive 2009/29/EC was the inclusion of a harmonized method of allowances allocation at EU level, being auction the main procedure for allocation. They were controlled through various regulations (Regulation 1031/2010, amended by Regulation 1210/2011 and Regulation 1143/2013).

For its part, Regulation 176/2014 amended Regulation 1031/2010, establishing the volume of gas emission allowances that would be auctioned in 2013-2020. Thus, in view of an excess of allowances in the market by the end of 2013 (the end of Phase II and beginning of Phase III), the European Commission proposed measures to avoid market imbalances. One of these measures was "backloading", a mechanism involving withdraw of about 900 million EUA from available volumes within the 2014-2016 period, reintroducing it in instalments in 2019 and 2020. However, the planned reintroduction –300 million EUA in 2019 and 600 million EUA in 2020 - as stated in Regulation 176/2014, was then thought to cause structural supply-demand unbalances. Therefore, those 900 million EUA were not to be auctioned in 2019 or 2020 but added to a market stability reserve (Decision 2015/1814).

In addition, other regulations aimed at intensifying emission reductions in the EU, have raised. For instance, the 2050 Low-Carbon Economy Roadmap towards a competitive low-carbon economy, the Climate & Energy Package (2013-2020), Directive 2018/410, issued to, once more, amend Directive 2003/87/EC, and Decision (EU) 2015/1814 with the purpose of enhancing cost-effective emission reductions.

Background in the research on emission allowances

Prior research lines analyzing emission allowances price, have focused on applying univariate or multivariate procedures. Univariate models, mainly apply ARIMA models and, in some cases, volatility models (8). Multivariate methods intend to justify the behaviour of emission allowances price through different variables, (2, 11, 12, 15). In this multivariate context, economic, energy and climatic variables are chosen for analysis.

Some economic variables focus on stock indices (11), macroeconomic and financial indicators (6) or business indices such as the Industrial production index (1, 7, 8). Their positive influence on allowances prices has been widely demonstrated, although depending on the variable itself and the study period.

In relation to energy factors, prices depending on different energy sources (renewable, hydroelectric, fossil), and fossil fuels (oil, coal and gas) are widely used. In general, research using energy prices study their positive relationship with emission allowances prices, while fossil fuel prices impacts are not as evident as the former (1, 7, 15, 19). Additionally, among climatic variables, temperature is mostly studied (1, 15).

In this context, numerous empirical studies have analyzed the behaviour of emission allowances prices in phases I and II. Applied research dealing with phase III, or all periods simultaneously, is scarce (22). In addition, many of these studies have focused on Europe and, in a smaller number, on other markets, such as the Nordic (19), Chinese (12) or American (21).

Methodology

In this work, multivariate models (VAR / VECM) were applied, considering, a priori, all variables as endogenous and each one affecting the others. Therefore, a VAR model (p) (Y_t) is defined according to its p lags (Y_{t-i}) weighted by the coefficient matrix A_i, by exogenous variables (X_t) affected by coefficient matrix B, and by error terms (e_t), i.i.d N(0, Ω).

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + BX_t + e_t$$

Thus, the VAR (p) model for the two studied variables is:

$$Y_{1t} = \beta_{10} + \beta_{11}Y_{1t-1} + \cdots + \beta_{1k}Y_{1t-p} + \alpha_{11}Y_{2t-1} + \cdots + \alpha_{1k}Y_{2t-p} + e_{1t}$$

$$Y_{2t} = \beta_{20} + \beta_{21}Y_{2t-1} + \cdots + \beta_{2k}Y_{2t-p} + \alpha_{21}Y_{1t-1} + \cdots + \alpha_{2k}Y_{1t-p} + e_{2t}$$

The VECM can be inferred based on this VAR model, with level and differences variables, in the following terms:

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta Y_{t-i} + B X_t + e_t$$

where:

ΔY_t = the differential operator (Y_t - Y_{t-1})

$\pi = -(I - \sum_{i=1}^{p} A_i)$ = a matrix with rank r containing the cointegration relations existing between the k variables

$\pi_i = -\sum_{j=i+1}^{p} A_j$ = the coefficient matrix for ΔY_{t-i}

Also, if the π matrix rank is r, being r < k, this matrix can be broken down into the product of two matrices (π **= β'**)

where:

α = a k x r matrix whose coefficients correspond to speed adjustment

β' = a r x k matrix, collecting the cointegration relations coefficients.

Therefore, in order to define the VAR or the VECM model, stationarity of each series in the first place, and their potential cointegration, had to be analyzed.

Variables and information sources

The information analyzed corresponds to monthly series, from January 2008 to July 2019 (139 months) obtained from various institutions. For emission allowances prices, the European trading platform for emission allowances (Sendeco2), was referenced. Regarding the economic factors, the EU-28 Industrial Production Index (IPI), The Baltic Dry Index (BDI) and the Purchasing Managers Index (PMI), were analyzed.

All historical data series cover the 139 months. The EU-28 Industrial Production Index, was calculated after information from Eurostat. The PMI and BDI indices, created by IHS Markit Economics and The Baltic Exchange respectively, were obtained through the financial web.

The European Industrial Production Index (IPI) was selected for being a relevant indicator of evolution undergone by the industrial productive activity. It eliminates price influence, allowing the macroeconomic situation to be characterized. BDI and PMI, novel variables in the analysis context of emission allowances price, also tightly related to the economic situation, have gained significant international impact. The BDI index, created in 1985, is related to ocean freight contracting for raw materials and bulk goods. Since economic evolution affects fright contracting, this index can be considered a world demand proxy variable. The European PMI constitutes an important indicator of business sentiment. Contrasting with the industrial production index, it considers future prospects contemplating preceding periods. The IPI takes a neutral value of 50, with higher levels implying activity progress and lower levels marking slowdowns. It constitutes the most widely used indicator –along with the Economic Sentiment Indicator (ESI)– for economic assessment (European Commission, European Business Cycle Indicators, 2nd Quarter 2017). Consequently, these variables and their evolution may affect the allowances price, since economic growth, related to these variables, influences greenhouse gases emissions.

Data on monthly prices of energy factors, was obtained from the World Bank information. Oil (Brent type), gas (European type) and coal, (average price in Australia and South Africa, main world coal markets) were considered. As these factors are priced in dollars for different energy units, they were converted to the same monetary and energy unit (€/Mwh), according to euro-dollar exchange rate, and the conversion of the International Energy Agency.

A priori, the price of fossil fuels is expected to influence the emission allowances prices, since fuel type and its level of use, could influence allowances demand. Thus, the cheaper but more polluting coal would cause greater demand for allowances, (Megawatt-hour). The use of gas, on the contrary, means lower emissions, but higher costs. Finally, brent oil produces higher emissions than gas but lower than coal, while being the most expensive per unit of produced energy.

Results

The results obtained were structured in different stages. Firstly, a descriptive analysis addressed behaviour and time relationship of emission allowances prices, fossil fuels prices and economic indices. Then, the VAR/VECM was estimated, contrasting and validating the model.

Descriptive analysis of fundamental factors

Emission allowances prices (EUA) have experienced two major trends, one decreasing trend from the beginning of 2008 to mid-2017 and, a rising trend from mid-2017, onwards. In this initial decreasing trend, monthly prices ranged between 27 and 3 €, reflecting non-stationary behaviour. After the sharp fall in 2008, these prices have maintained certain levels through different periods: 10-15 € in 2008-2011, 3-10 € in 2013-2016, and around 5 € in 2016-2017. Some institutions and researchers justified the EUA price drop in terms of a supply *vs.* demand imbalance caused by different factors: lower energy consumption as a result of the economic crisis and the collapse of industrial activity and consequently, of CO_2 emissions. However, an increasing trend has been observed since mid-2017 in terms of the EUA price, achieving almost 27 € (figure 1).

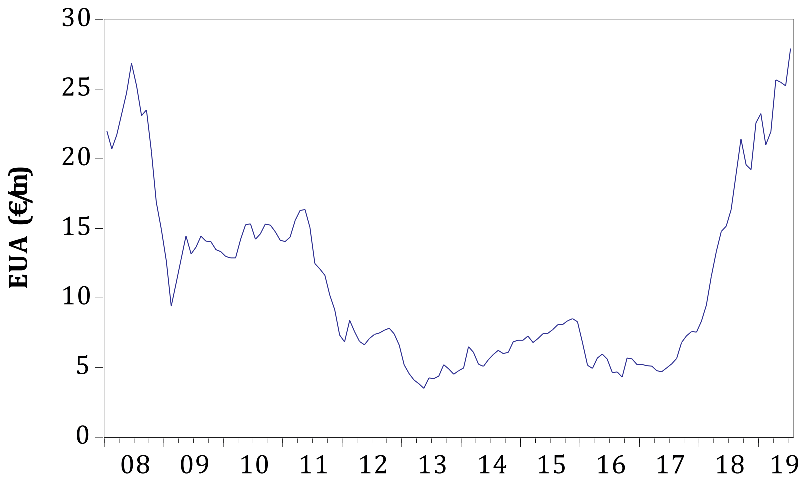


Figure 1. Monthly allowances emission prices (EUA) (2008-2019).

Figura 1. Precios mensuales derechos emisión (EUA) (2008-2019).

This situation brought a significant emission rights surplus in the system, which in turn caused prices to fall, meaning that these prices did not have a disincentive effect in relation to the use of less contaminating energies. Generous national free emission allowances in previous negotiation periods, as well as the use of cheap international emissions reduction credits or policies, oriented to energy efficiency and renewable energies sources (25), had significant effects.

Many factors may have influenced this change in trend. The recovery in industrial activity has meant higher emissions and has therefore caused a higher industrial demand of CO_2 emission allowances. Approved measures by the end of 2016, regulating the market and addressing emission rights surplus with the Market Stability Reserve, is another reason worth noting. Furthermore, increasing energy factor prices have also affected the EUA price.

Finally, the application of the new legal framework since January 2018 (Directive 2014/65/EU), with new financial agents to operate and additional legal requirements, is likely to result in an increasing demand for emission allowances.

Therefore, emission allowances prices present an important variation (3-27 €) reflecting non-stationarity in the considered period. The same behaviour is shown by the series corresponding to energy factors, oil (BRENT), coal (COAL) and gas (GAS), and by those related to the economic indexes, IPI, PMI and BDI. However, the IPI and PMI variables showed to be somewhat more stable than the BDI index (figure 2).

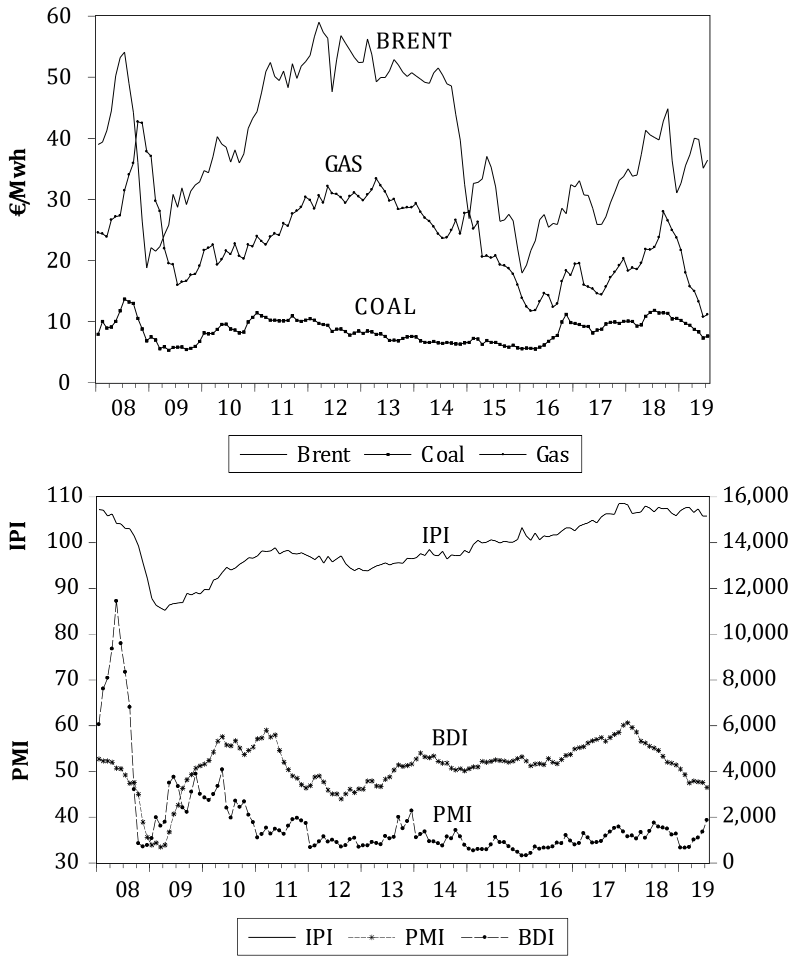


Figure 2. Energy and economic factors evolution (2008-2019).

Figura 2. Evolución de los factores energéticos y económicos (2008-2019).

VAR/VECM Model estimation

Endogenous variables are constituted by emission allowances prices (EUA), energy variables prices (BRENT, COAL, GAS) and economic indices (IPI, PMI, BDI). All variables were transformed into logarithms, reducing their variability (variables with initial "L"). The VAR/VECM model estimation made it necessary to study stationarity and the possibility of cointegration of these series. In summary, if the series resulted to be stationary, a level VAR model should be chosen, but if the series were integrated but not cointegrated, a difference VAR model had to be applied. Finally, if the series were integrated and cointegrated, a VEC model (Vector error correction) ought to be used.

The stationarity analysis was performed by contrasting the existence of unit roots, for series in level and in first differences. The Dickey-Fuller Augmented (ADF) and the Philips-Perron (PP) tests, with a constant term, were used. In general, the "level series" concluded that the null hypothesis of the existence of a unitary root, was not rejected, reflecting lack of stationarity, while for the "series in first differences" the null hypothesis was rejected, so the series were integrable of order 1, I (1) (table 1).

Table 1. Unit root tests, in levels and differences (Δ), (t-statistic and p-value in parentheses).

Tabla 1. Test raíces unitarias, en niveles y diferencias (Δ), (t-estadístico y p-value en paréntesis).

Energy Variables	Series	Dickey-Fuller Augmented	Philips-Perron	Economic Variables	Series	Dickey-Fuller Augmented	Philips-Perron
LBRENT	Level	**-2.42**	**-1.80**	LBDI	Level	**-2.58**	**-2.42**
		(0.13)	(0.37)			(0.09)	(0.13)
	Δ	**-8.80**	**-8.61**		Δ	**-11.25**	**-12.54**
		(0.00)	(0.00)			(0.00)	(0.00)
LCOAL	Level	**-2.54**	**-2.49**	LIPI	Level	**-1.26**	**-1.73**
		(0.10)	(0.12)			(0.64)	(0.40)
	Δ	**-9.84**	**-9.89**		Δ	**-9.46**	**-10.35**
		(0.00)	(0.00)			(0.00)	(0.00)
LGAS	Level	**-1.52**	**-1.69**	LPMI	Level	**-3.09**	**-2.82**
		(0.52)	(0.43)			(0.04)	(0.06)
	Δ	**-9.18**	**-9.39**		Δ	**-5.53**	**-5.67**
		(0.00)	(0.00)			(0.00)	(0.00)
LEUA	Level	**-1.13**	**-1.14**				
		(0.69)	(0.69)				
	Δ	**-8.28**	**-8.24**				
		(0.00)	(0.00)				

For cointegration series analyses, a regression model with the considered variables (9) and the existence of unit roots in the contrasted residues, was constructed. The Augmented Dickey-Fuller test (ADF) did not reject the null hypothesis of the existence of a unit root and, therefore, showed lack of stationarity and non-cointegration, resulting in integrable series of order 1, but not I (0) (table 2).

Table 2. Regression model and residuals test.

Tabla 2. Modelo de regresión y contraste de residuos.

Dependent Variable: LEUA					**RESIDUALS** (Critical value, 4.48 (5%) (variables=7, sample=137)			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Null Hypothesis: unit root		t-Statistic	Prob.
LBRENT	-0.61	0.18	-3.30	0.00	Augmented Dickey-Fuller test		-1.886	0.337
LCOAL	0.94	0.17	5.70	0.00	Test, critical values:	1% level	-3.479	
LGAS	0.19	0.20	0.93	0.35		5% level	-2.883	
LIPI	0.22	0.43	0.50	0.62		10% level	-2.578	
LPMI	-0.57	0.48	-1.17	0.24	Engle-Granger test (D(Residuals)=β*Residuals(-1)), (β= -0.073)			0.06
LBDI	0.43	0.05	8.80	0.00				

This non-cointegration led to a VAR model, although after converting the original series to stationary, differentiating previously logarithm transformed variables (variables with initial "D").

Optimum lag lengths estimation in the VAR model, was also necessary. Excessive lag lengths would unnecessarily reduce degrees of freedom, but insufficient lag lengths would result in a lack of specification, probably affecting residual autocorrelation. Therefore, various criteria to select lag number for the variables analyzed, were applied: one lag for criteria like Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ), or three lags for the LR sequential test. Considering that the choice must be consistent with the non-autocorrelation residuals, property verification with both alternatives, was also necessary. Consequently, considering the Akaike and Schwarz criteria and the goodness level, the VAR model with three lags, was finally chosen (table 3).

Table 3. VAR Lag Order Selection (* lag order selected by the criterion, 5% level).

Tabla 3. Selección de retardos modelo VAR (* orden retardo seleccionado por criterio, 5% nivel).

Criteria (LR: sequential modified test; AIC: Akaike; SC: Schwarz; HQ: Hannan-Quinn).

Lag	LogL	LR	AIC	SC	HQ
1	1,252.05	NA	-20.56*	-19.40*	-20.09*
2	1,287.15	61.79	-20.32	-18.01	-19.38
3	1,326.62	64.76*	-20.16	-16.69	-18.75
4	1,352.70	39.69	-19.77	-15.14	-17.89

Next, VAR model stationarity, a condition analyzed through characteristic polynomial roots, was contrasted. Given that these values were lower than one and included within the unit circle, their stability was verified. In addition, as in the VAR model the variables may have been related, contrasting their causality in order to find their interaction level (Annex A1, Table A1_1), was important. Therefore, the Granger test was applied, variable pairwise, using lags order (3) in the explanatory variable (table 4).

Table 4. Causality Granger, variables pairwise (Lags: 3).

Tabla 4. Causalidad de Granger entre variables (retardos: 3).

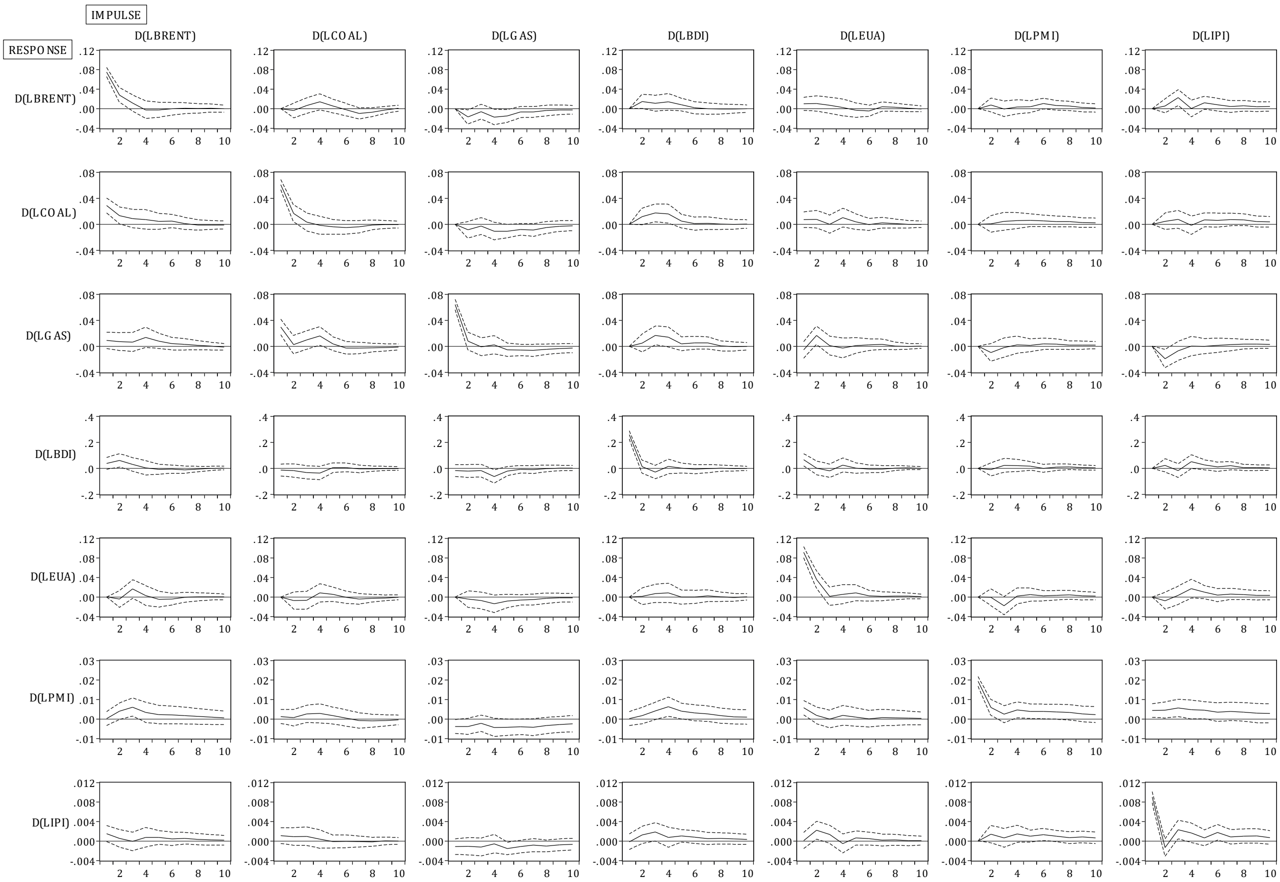
	Null Hypothesis (doesn't Cause)	Prob.		Null Hypothesis (doesn´t Cause)	Prob.
D(LEUA)	**D(LBRENT) on D(LEUA)**	**0.005**	**D(LGAS)**	**D(LCOAL) on D(LGAS)**	**0.009**
	D(LEUA) on D(LBRENT)	0.362		D(LGAS) on D(LCOAL)	0.917
	D(LGAS) on D(LEUA)	0.283		**D(LIPI) on D(LGAS)**	0.489
	D(LEUA) on D(LGAS)	0.140		D(LGAS) on D(LIPI)	0.569
	D(LCOAL) on D(LEUA)	0.538		**D(LPMI) on D(LGAS)**	0.902
	D(LEUA) on D(LCOAL)	**0.058**		D(LGAS) on D(LPMI)	0.576
	D(LIPI) on D(LEUA)	0.421		**D(LBDI) on D(LGAS)**	0.157
	D(LEUA) on D(LIPI)	0.074		D(LGAS) on D(LBDI)	**0.029**
	D(LPMI) on D(LEUA)	0.339	**D(LCOAL)**	**D(LIPI) on D(LCOAL)**	0.094
	D(LEUA) on D(LPMI)	0.764		D(LCOAL) on D(LIPI)	**0.033**
	D(LBDI) on D(LEUA)	0.167		**D(LPMI) on D(LCOAL)**	0.388
	D(LEUA) on D(LBDI)	0.894		D(LCOAL) on D(LPMI)	0.062
D(LBRENT)	**D(LGAS) on D(LBRENT)**	0.092		**D(LBDI) on D(LCOAL)**	**0.028**
	D(LBRENT) on D(LGAS)	0.204		D(LCOAL) on D(LBDI)	**0.054**
	D(LCOAL) on D(LBRENT)	0.438	**D(LIPI)**	**D(LPMI) on D(LIPI)**	**0.005**
	D(LBRENT) on D(LCOAL)	0.239		D(LIPI) on D(LPMI)	**0.003**
	D(LIPI) on D(LBRENT)	0.061		**D(LBDI) on D(LIPI)**	**0.004**
	D(LBRENT) on D(LIPI)	0.124		D(LIPI) on D(LBDI)	0.411
	D(LPMI) on D(LBRENT)	0.090	**D(LPMI)**	**D(LBDI) on D(LPMI)**	**0.039**
	D(LBRENT) on D(LPMI)	**0.034**		D(LPMI) on D(LBDI)	0.810
	D(LBDI) on D(LBRENT)	**0.030**			
	D(LBRENT) on D(LBDI)	0.061			

Therefore, the past value D(LBRENT),influenced D(LEUA) and D(LPMI), while in turn, the variable D(LEUA) affected D(LCOAL). Likewise, a relation between the energy variable D(LCOAL) with D(LGAS) and with D(LIPI), was found.

Furthermore, the variables (D(LCOAL), D(LGAS) and D(LBRENT)) influenced the D(LBDI) index and, by contrast, D(LBDI) had an impact on (D(LBRENT) and D(LCOAL)) and on the economic factors D(LPMI)) and D(LIPI)). Finally, (D(LPMI)) and D(LIPI)) related to each other.

The Impulse-Response Function is a procedure based on VAR model reformulation, as moving averages. It analyzes the time effect that an impulse or alteration in each variable would produce on the remaining variables, given the dynamic interrelation among all variables. This type of analyses offered by the VAR model, constitute statistical interpretations of the responses of one variable after the impact of another.

In general, the response of each variable to impacts on its own innovations, is positive and decreasing over time, while the response of each variable to impacts coming from other variables, reflects different behaviours (figure 3).



Cholesky Ordering: D(LBRENT), D(LCOAL), D(LGAS), D(LBDI), D(LEUA), D(LPMI), D(LIPI).

Figure 3. Response to Cholesky (One S.D. Innovations ± 2 S.E.).

Figura 3. Función impulso-respuesta, Cholesky (Una S.D. Innovaciones ± 2 S.E.).

Thus, variables such as D(LBRENT), D(LEUA) and D(LBDI) usually cause a positive response in the rest of the variables, unlike the impact of D(LGAS), usually negative. Also, the impact of D(LIPI) or D(LPMI) positively affected the remaining variables, except for D(LGAS) and D(LEUA) which had an initial negative behavior, but a final positive performance.

D(LCOAL) impacts had different responses depending on the variable. It negatively impacted D(LBDI), while), it showed positive impacts on variables like D(LGAS), D(LIPI) and D(LPMI or temporal opposite effects (initially negative and then positive), on D(LEUA) and D(LBRENT).

The model was validated by means of residual analysis, contrasting the existence of non-autocorrelation, normality and homoscedasticity. To study autocorrelation, the Portmanteau and Lagrange tests were applied, not rejecting the null hypothesis of correlation absence.

Residuals normality was assessed using Cholesky Orthogonalization and the Jarque-Bera test for skewness and kurtosis. The null hypothesis was rejected and, therefore, residuals resulted not normally distributed. However, lack of normality in VAR models does not affect their validity (14). For homoscedasticity analysis, the White test without cross-terms was applied, and the null hypothesis of homoscedasticity was not rejected.

Discussion

Estimating carbon price constitutes an efficient strategy for reducing emissions and their negative impact (10). Even though some methods have attempted to estimate this price, the creation of an emissions market has allowed to precisely know this value, facilitating negotiations with emission allowances. Therefore, with a determined market price, relationships between emission allowances pricing with other variables (economic and energy) can be estimated. This approach identifies variables with major influence, their variations, and forecasts emission allowances prices.

In this context, approaches within the multivariate context of time series, should be considered. Some authors apply error correction models (VECM), considering the existence of cointegration variables (11, 19), while others prefer VAR models with non-cointegration variables (Chevalier, 2011b; Zeng *et al.*, 2017; Jiang *et al.*, 2018, among others).

Many significant factors like the procedure, the geographic context, or the model estimation period conditioned the obtained results. For this particular study case, the analyzed information comprised from 2008, period in which the emission allowances negotiations actually began in the EU (phase II), to 2019.

Regarding the interaction among emission allowances prices with the rest of the variables, causalities of D(LBRENT) on D(LEUA), and of D(LEUA) on D(LCOAL), were verified.

In particular, for D(LEUA), the impulse-response function analysis showed dependency on the impacting variable, while responses to D(LGAS) and D(LBDI),were negative and positive, respectively. For the remaining variables, D(LEUA) response was practically similar, but of opposite signs. These results are in accordance with those obtained by other authors, also stating the relationship among emission allowances prices and their past values (11, 12). In addition, Hu *et al.* (2018) showed, for the European market, the relationship with Brent oil and stock indices in the period 2014-2015, while Jiang *et al.* (2018) did not consider the influence of oil in the 2013-2017 period for the Chinese market.

Another research on the European market during the 2008-2009 period divided into subperiods, showed that the significance of brent, gas and coal prices on emission allowances prices, depended on the subperiod considered (7). Later, for the European market during 2005-2016, and three sub-periods, another study showed how fossil fuels (oil, gas and coal) and several financial market indexes influenced emission allowances prices, according to the subperiod analysed (23).

Likewise, Alexeeva-Talebi (2011) applied a VECM model in different European countries in the period 2005-2007 and observed that Brent price only influenced emission allowances prices in some countries. Finally, Koch *et al.* (2014) concluded that for the European market in the 2008-2013 period, emission allowances prices were only influenced by the economic satisfaction index and the price of gas and electricity provided by renewable sources.

Considering energy variables, certain literature discrepancy about their influence on emission allowances price is evident, but, in general, they coincide in the relationship with some fuels.

Finally, some authors state that economic variables like stock market indices, industrial production, economic satisfaction, futures and financial asset returns, affect emission allowances prices. In this work, the industrial production index and two novel variables, the European purchasing management index and the Dry Baltic index have been used, being this last variable, more significant regarding the emission allowances price.

Conclusions

This study investigated the relationship between emission allowances prices and energy and economic variables, by modelling their behaviour.

The analysis was approached under a multivariate basis, considering energy and economic variables. It was concluded that energy variables partly explain the behaviour of those prices, and their inclusion in any study, is recommended. Regarding economic variables, the Dry Baltic index (BDI) resulted a significant variable, related to energy factors. The Industrial Production Index (IPI) and the European Purchasing Management Index (PMI), resulted to be less important.

These conclusions confirm the studied energy variables and the BDI to be significant for explaining variations in the emission allowances prices. These conclusions may lead future research, not only regarding analysis procedures, but also confirming interrelation between some variables.

In order to achieve stationarity, the original variables required transformation, and the lack of cointegration led to estimating a VAR model, including temporal variable interrelation. Several conclusions related to causality and impulse-response functions were obtained. One conclusion stated that variations in emission allowances price are mainly conditioned by prior values and by some variables, mainly brent, gas and BDI.

Finally, emission allowances prices resulted to be sensitive to other variables impact, although in a heterogeneous fashion; Gas impacted negatively and BDI, positively. The remaining variables, such as brent petroleum and coal, and the economic factors (IPI and PMI) had somewhat similar behaviour, with changing sign, firstly negative and subsequently becoming positive). This sign change in the emission allowances price variation, may be due to an initial demand contraction. However, when price growth consolidates over time, the consequent demand turns greater, finally causing increasing price variations.

Supplementary tables

https://drive.google.com/file/d/1qfhWCF56M2GfHtx6Bua4igHFKFTW_Jef/view?usp=sharing

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Acknowledgements

This article was supported by project RTI2018-093791-B-C21, Ministry of Science, Innovation and Universities (Spain) and FEDER (European Union).

Annex A1

Tabla A1_1. Estimación modelo VAR (3) (estadístico t-en paréntesis).
Table A1_1. Estimation VAR (3) model (t-statistic in parenthesis).

Variables	D(LEUA)	D(LBRENT)	D(LCOAL)	D(LGAS)	D(LBDI)	D(LIPI)	D(LPMI)
D(LEUA(-1))	0.392	-0.005	0.012	0.191	-0.079	0.014	-0.012
	(3.886)	(-0.062)	(0.159)	(2.423)	(-0.265)	(1.325)	(-0.521)
D(LEUA(-2))	-0.102	0.076	-0.061	-0.109	-0.202	0.008	-0.019
	(-0.950)	(0.854)	(-0.771)	(-1.299)	(-0.641)	(0.704)	(-0.775)
D(LEUA(-3))	0.046	-0.113	0.070	-0.034	0.189	-0.011	-0.014
	(0.449)	(-1.343)	(0.928)	(-0.426)	(0.636)	(-1.118)	(-0.601)
D(LBRENT(-1))	-0.006	0.343	0.031	0.094	0.818	0.000	0.039
	(-0.048)	(3.370)	(0.346)	(0.979)	(2.270)	(0.022)	(1.373)
D(LBRENT(-2))	0.232	-0.112	-0.003	-0.038	0.412	-0.021	0.019
	(1.819)	(-1.055)	(-0.027)	(-0.382)	(1.097)	(-1.650)	(0.636)
D(LBRENT(-3))	-0.231	-0.208	-0.028	-0.067	0.123	-0.008	-0.024
	(-1.836)	(-1.993)	(-0.295)	(-0.682)	(0.332)	(-0.632)	(-0.830)
D(LCOAL(-1))	-0.066	0.044	0.331	0.060	-0.168	0.025	0.017
	(-0.422)	(0.341)	(2.879)	(0.497)	(-0.368)	(1.589)	(0.461)
D(LCOAL(-2))	0.044	0.064	-0.056	0.240	-0.412	0.016	0.022
	(0.288)	(0.503)	(-0.489)	(1.992)	(-0.911)	(0.992)	(0.617)
D(LCOAL(-3))	0.218	0.316	0.074	0.230	-0.183	0.001	0.026
	(1.471)	(2.563)	(0.672)	(1.981)	(-0.418)	(0.071)	(0.758)
D(LGAS(-1))	-0.085	-0.220	-0.113	0.064	-0.303	-0.014	-0.033
	(-0.636)	(-1.990)	(-1.146)	(0.614)	(-0.776)	(-1.060)	(-1.076)
D(LGAS(-2))	-0.132	0.089	0.075	-0.015	-0.095	-0.005	0.016
	(-1.050)	(0.851)	(0.801)	(-0.149)	(-0.257)	(-0.380)	(0.565)
D(LGAS(-3))	-0.074	-0.207	-0.114	0.091	-0.797	0.004	-0.017
	(-0.591)	(-1.983)	(-1.227)	(0.925)	(-2.162)	(0.336)	(-0.603)
D(LBDI(-1))	0.005	0.057	0.046	0.018	0.047	0.005	0.007
	(0.139)	(2.079)	(1.854)	(0.698)	(0.479)	(1.390)	(0.881)
D(LBDI(-2))	0.035	0.019	0.048	0.065	-0.163	0.007	0.010
	(1.047)	(0.690)	(1.904)	(2.441)	(-1.636)	(1.906)	(1.312)
D(LBDI(-3))	0.027	0.042	0.043	0.052	0.062	0.002	0.013
	(0.740)	(1.391)	(1.621)	(1.832)	(0.583)	(0.539)	(1.557)
D(LIPI(-1))	-0.850	0.426	0.485	-1.876	2.706	-0.182	0.357
	(-0.866)	(0.523)	(0.667)	(-2.446)	(0.939)	(-1.828)	(1.582)
D(LIPI(-2))	0.853	1.733	0.290	-0.746	-2.975	0.144	0.408
	(0.821)	(2.011)	(0.376)	(-0.919)	(-0.975)	(1.365)	(1.706)
D(LIPI(-3))	1.677	-0.662	-0.769	-0.251	2.121	0.125	0.099
	(1.610)	(-0.765)	(-0.998)	(-0.308)	(0.693)	(1.181)	(0.411)
D(LPMI(-1))	-0.033	0.393	0.025	-0.493	-0.522	0.073	0.306
	(-0.073)	(1.063)	(0.074)	(-1.414)	(-0.398)	(1.614)	(2.984)
D(LPMI(-2))	-0.884	-0.392	0.125	0.184	0.603	0.020	-0.021
	(-1.834)	(-0.980)	(0.350)	(0.487)	(0.426)	(0.403)	(-0.186)
D(LPMI(-3))	0.562	0.125	0.149	0.426	0.698	0.066	0.146
	(1.316)	(0.352)	(0.472)	(1.276)	(0.556)	(1.532)	(1.485)
R-squared	0.274	0.376	0.288	0.298	0.203	0.324	0.420
Akaike AIC	-1.795	-2.167	-2.398	-2.288	0.360	-6.371	-4.732
Schwarz SC	-1.325	-1.697	-1.927	-1.817	0.830	-5.900	-4.262