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Emission trading in a high dimensional context: to what extent are carbon markets integrated with the broader system?

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Abstract

The EU ETS represents the cornerstone of the EU climate policy framework. While most of the studies focus on the determinants of carbon price, this work will provide further insights into the influence of European Emission Allowance (EUA) prices on carbon dioxide trends and variables of the economic-financial-climate-environmental system considering a large set of time series. Results highlighted how CO_2 appears to be more influenced by commodity prices, climate variables, and past industrial performances. Furthermore, a shock in carbon prices could potentially exert significant turbulence on the carbon dioxide series, fading in intensity as time goes by. Overall, there appears to be a net positive effect on the influence of carbon prices on the system. However, robustness checks identified how the impact of carbon price on CO_2 and other variables of the model is still weak. This work sheds light on the EU ETS's influence on a set of multidimensional variables. Still, overlapping national policies appear to interfere with the EU ETS effectiveness in the EU.

Keywords EU ETS · Emission trading · Hierarchical VAR · Impulse-Response

JEL Classification Q52 · Q58 · C54

1 Introduction

An appropriate account of the social costs of carbon is still an open issue and a perceived hurdle to achieving a societal transition toward sustainability (Pearce, 2003). In the 34 IPCC scenarios, carbon price estimates range from US$37 to US$67 per tonne of CO_2 in 2020, whereas in 2050, it would be US$127-US$305 (IPCC, 2014; Tvinnereim & Mehling, 2018). However, if carbon pricing could generate revenue

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flows and reduce the overall tax burden, more flexible pricing mechanisms could likely imply fewer adverse effects on competitiveness (OECD, 2016). While improvements in the so-called carbon price gap signal a better use of market-based instruments reducing CO_2 emissions, there are concerns that the current rate of change could meet the ambitious targets of the Paris Agreements (OECD, 2018). On the other hand, the Commission estimated €260 billion to comply with the EU Green Deal objectives by 2030. The European Union launched the European Emission Trading Scheme (EU ETS) in 2005. The mechanism has been functioning for over a decade, providing a price primarily to CO_2 emissions for specific categories of enterprises within the European territory. As such, the EU ETS has attracted the interest of policymakers and the academic world (Convery, 2008; Ji et al., 2019). Several streams of research (Chevallier, 2011a; Convery, 2008; Ji et al., 2019) have tried to disentangle the drawbacks, strengths, and determinants of the European Union Allowance (EUA) price.

Some contributions have endeavored to assess the effect of the EU ETS' carbon price behavior on GHG emission generation (for a review, see Sect. 2). Grosjean et al. (2016) proved that exogenous shocks undermining price stability might come from different sources (e.g., economic recession, overlapping policies, and a large influx of Certified Emission Reduction/Emission Reduction Units). Furthermore, while adjustment mechanisms, such as the Market Stability Reserve (MSR), have been implemented, further investigations of their effects favoring GHG abatement would deliver a more extensive understanding of the functioning of those mechanisms (Azarova & Mier, 2021). In its rough structure, the MSR ensures a specific range of EUA price variation via automatically injecting or retrieving permits whenever the quantity in the market reaches certain (lower or upper) thresholds. Indeed, as the process is triggered automatically once the quantity in the market reaches bounds, the system will be subject to a shock that affects prices and other connected variables. On the other hand, other mechanisms (i.e., price roof/floor) act directly on prices (Andor et al., 2016).

In this context, this present work will test the effects of possible exogenous shocks of carbon prices on carbon emissions. The analysis will be expanded to test the response of economic, financial, energy, and climate dimensions. Those are relevant aspects that influence and are influenced by carbon emissions and carbon prices. This work will be carried out by adopting a vector autoregressive (VAR) framework encompassing an extensive array of time series data ranging from economic indicators (e.g., industrial production) to energy metrics (such as natural gas, coal, crude oil, and electricity), and extending to financial and climate data (including temperatures, rainfall patterns, and wind speed). In a much broader perspective, the paper will analyze the current state of the interplay among carbon price mechanisms and other relevant dimensions (e.g., industry, energy, finance) by assessing their response to a shock on EUA prices considering the broader system (e.g., climate, environmental dimension) (Schusser & Jaraitė, 2018). This paper employs the Hierarchical Vector Autoregressive (HVAR) model that has been proven to better address analyses with a growing number of variables with respect to other VAR models (Nicholson et al., 2020). Indeed, the paper can be included in the research endeavors to frame machine learning techniques within economic analysis and policy evaluation. In some cases, when dealing with high-frequency or high-dimensional data, machine-learning techniques appear to fare better with respect to standard econometrics (Athey, 2017; Athey & Imbens, 2017; Varian, 2014). Results highlighted how EUA prices still play a relatively weak role in influencing the other variables of the system. This might be related to national policies that overlap with the EU ETS. However, with this kind of analysis, it is not possible to consider the mediated effect of carbon price on emission through other variables. The work feeds the literature on the effectiveness of carbon prices on carbon emissions from a non-linear perspective. While most studies focus on one or a few factors of the relationship between the carbon price and the economic-environmental system, this work considers a set of multiple factors (e.g., economy, finance, energy, climate). Furthermore, most studies on the effectiveness of carbon price in influencing CO_2 have been carried out at the micro level. This work provides further insights into analyzing the relationship for the EU as a whole. To policymakers, this work might provide valuable insights into the current role of carbon prices in the socio-environmental system accounting for the different nature of the variables. For a previous version of this work see (Quatrosi, 2023). The work proceeds with Section 2, which reviews the literature on emission trading, focusing on studies on the effectiveness of carbon prices. Section 3 describes the data and methodology. Section 4 presents the results of the Impulse-Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). Sections 5 and 6 will provide comments and discussions on the results with conclusions and implications for policymakers.

2 Literature review

Most of the literature on emission trading has focused on finding the determinants of carbon price as being influenced by weather (temperature, extreme weather events), other commodity prices (i.e., oil, gas), other carbon markets, industrial productivity, financial markets[1] (e.g., commodities) (Alberola et al., 2008; Oberndorfer, 2009; Creti et al., 2012; Aatola et al., 2013; Koch et al., 2014; Ji et al., 2019; Soliman & Nasir, 2019; Zhu et al., 2018). Aside from the influence of those variables, other sources can be tracked down to possible conflicting policy aims between the EU ETS and national policies (e.g., waterbed effect) (Bruninx & Ovaere, 2022; Lecuyer & Quirion, 2013; Perino et al., 2019; Shahnazari et al., 2017).

Another stream of literature investigated the influence of carbon prices on different variables. Some studies at the country level highlighted how the EU ETS has been effective in abating emissions, mainly in the early stages of the Scheme (Anderson & Di Maria, 2011; Ellerman & Feilhauer, 2008). In Germany and the UK, setting a carbon price has been proven to be more effective in abating emissions with respect to subsidies to renewable energy sources (Gugler et al., 2021). A recent contribution highlighted how an increase in carbon price would lead to increased costs for electricity, production, and, in turn, prices in Spain (Arcos-Vargas et al., 2023). Carbon and energy markets are interconnected (Andrzejewski

[1] EUAs are considered particular category of financial instruments under MiFID II Regulation (Directive 2014/65/UE du Parlement européen et du Conseil du 15 mai 2014 concernant les marchés d'instruments financiers et modifiant la directive 2002/92/CE et la directive 2011/61/UE Texte présentant de l'intérêt pour l'EEE, 2014) pursuant to point (11) of Section C of Annex I of that directive. Derivatives of emission allowances are listed under point (4) of Section C of the said Annex.

et al., 2019; Ma et al., 2021). However, the cost pass-through of CO_2 prices into electricity prices could compromise the connection between the carbon and commodity markets (Freitas & Silva, 2015). Carbon price and weather (e.g., temperature, rainfall) are proven to be correlated, especially at a high frequency (Feng et al., 2011). Carbon price responds to abrupt changes in temperature caused by climate change (Batten et al., 2021). There is no concrete study on the relationship between wind rainfall and carbon prices (Chevallier, 2011b). However, it can be inferred that more favorable conditions for renewable energy might reduce emissions and thus reduce carbon prices.

At the micro level, studies have investigated the influence of carbon prices on firms' performances. A consistent amount of studies on firms subject to the EU ETS showed how, despite effectively reducing emissions, being included in the scheme did not affect their economic performances (Ellerman & Buchner, 2008; McGuinness & Ellerman, 2008; Martin et al., 2016 Dechezleprêtre et al., 2018; Marin et al., 2018; Löschel et al., 2019; Locatelli et al., 2022). A study on Chinese enterprises found that emission trading can increase corporate total factor productivity (Cheng & Meng, 2023). Other studies on firms highlighted how emission trading could affect firms' propensity to innovate (Teixidó et al., 2019). The literature on the relationship between carbon price and stock returns identifies a *carbon premium* for those enterprises that emit. Firms that emit face a higher carbon risk as they will pay a higher price for carbon allowance; therefore, investors require a higher return on the stock (Oestreich & Tsiakas, 2015). However, an inverse relationship has been proved between carbon prices and stock returns for companies that have to buy emissions allowances (Millischer et al., 2023).

The review highlighted how studies on the effectiveness of carbon prices had analysed the influence of the EU ETS on one or a few dimensions. They proved the effectiveness of carbon prices in reducing emissions without endangering economic performance. However, despite the effective decreasing trend in CO_2 over the last decade, it is pretty hard to trace the direct effect of the EU ETS considering the multiple factors involved (Brink & Vollebergh, 2020). Considering the inverse relationship between carbon and financial markets, a high carbon price will lead to a drop in financial indexes. The higher the percentage of firms that buy allowances, the higher the possible effect. Commodity, electricity, and carbon prices are correlated; thus, an increase in EUA prices should lead to an increase in energy prices. However, if the price of some fuel increases, the energy mix will switch to a much cheaper fuel. Thus, an increase in carbon price should lead to an overall increase in fuel prices but with mixed magnitude related to the possibility of fuel switching. The same should be valid for the electricity market save pass-through costs. There is a relationship between temperature changes and carbon prices. However, the literature lacks specific studies on rainfall and wind speed. However, it can be inferred that favorable weather conditions for renewable energy sources should, in principle, reduce emissions and thus increase carbon prices.

In this framework, this work can be included in the stream of literature that tries to assess the effectiveness of carbon prices. Unlike other studies, this work analyses the influence of carbon prices on a large set of variables, ranging from economic, financial, energy, and climate dimensions. Furthermore, most of the works in the

Table 1 Summary statistics of the series

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max	Median	St. Dev
Kilian Index	-163.170	-61.682	-32.285	12.445	188.060	-32.285	68.268
Brent	30.700	56.458	76.060	108.208	132.720	76.060	26.946
CO_2	242.407	275.695	296.484	319.891	358.932	296.484	28.099
EUA	3.538	5.887	8.093	14.613	26.881	8.093	6.003
Max Temperature	7.244	13.483	20.681	26.845	30.958	20.681	7.072
Tot Rainfall	0.053	0.086	0.102	0.113	0.145	0.102	0.018
Min Temperature	-13.793	-3.662	1.067	7.840	11.989	1.067	6.779
Wind Speed 10mt	2.940	3.330	3.643	3.956	4.616	3.643	0.401
Dutch TTF	3.910	6.692	8.795	11.262	15.930	8.795	2.834
North Pool Electricity	9.550	28.587	33.925	43.680	81.650	33.925	12.194
STOXX50E	1,976.230	2,665.525	3,025.670	3,362.532	3,825.020	3,025.670	433.066
Rotterdam Coal Futures	44.300	73.113	83.850	95.025	218.000	83.850	28.452

literature test the effectiveness of carbon prices on emissions at the micro level. This work tries to provide a macro perspective analysing the effect of a shock on carbon prices on emissions for the EU as a whole.

3 Data and methodology

3.1 Data

To tackle the different scales and units of measures of the variables, the series will be standardized to refine the subsequent analyses better (James et al., 2013). Table 1 summarizes the main statistics for the series. Monthly data will be considered for the analysis for a decade (2008–2019). Data on monthly EUA stock prices are taken from ICAP,[2] SendeCO2,and Jiménez-Rodríguez (2019). Aggregated monthly CO_2 trends have been estimated from data on energy consumption (e.g., Gross Inland Deliveries) for the 31 Countries and eight fuels (four primary and four secondary) from the Eurostat database following the methodology in Eggleston et al. (2006)[3] (so-called Reference Approach). To proxy for industrial production, the Global Index of Real Economic Activities[4] (e.g., Kilian Index) as conceived in Kilian (2009) and adjusted following Kilian (2019); Kilian and Zhou (2018), will be employed as a better measure of economic activity with respect to conventional indexes (e.g., real GDP, industrial production). The index is based on percentage changes in voyage shipping of industrial commodities (various bulk dry cargoes consisting of grain, oilseeds, coal,

[2] https://icapcarbonaction.com/en/

[3] The dataset is available upon request.

[4] The index is available in the Kilian's personal webpage and updated monthly by the Federal Reserve Bank of Dallas, see https://www.dallasfed.org/research/igrea

iron ore, fertilizer, and scrap metal). Those shipping are differentiated according to size and route and adjusted for US CPI inflation. The variation of this index is proportional to the variation in the volume of shipping of industrial commodities. To include the financial market side, the EURO STOXX50 index provides a composite measure of value for the biggest Eurozone enterprises in the stock market. The index is designed by STOXX and retrieved from Yahoo Finance.[5] For commodity prices, natural gas and oil come from the World Bank Commodity Price Data repository for the Netherlands Title Transfer Facility[6] (Dutch TTF) and Brent, respectively. Electricity prices are those of the Nord Pool Power Market (Nord Pool Electricity) encompassing Northern and Baltic regions. Data on the average price of the Rotterdam Coal Futures from the ICE market will be considered to proxy coal prices at the EU level. The climate and weather variables considered in the model are the monthly averages of temperatures (i.e., Min, Max Temperature), rainfall (Tot Rainfall), and wind speed measured at 10 m from the surface (Wind Speed 10 mt). Those data are retrieved from the IEA Weather Energy Tracker, held by the International Energy Agency (IEA) and the Mediterranean Centre for Climate Change (CMCC). As the IEA database contains country-level data, the series employed has been computed by averaging the values of the 31 Countries under the ETS for this analysis.

Tests on stationarity will be commented on later (Table 2), and the preliminary analysis will proceed with the correlation matrix of the series. As it is possible to appreciate (Table 3), there are quite a few high correlations between temperature and wind speed. CO_2 shows a significant but negative correlation with the temperature set and a positive with industrial production and commodities (e.g., natural gas price, oil, electricity) for the variables of interest. A relatively weak but positive correlation exists with EUA prices, and a negative correlation exists with the STOXX index. On the other hand, EUA prices positively correlate with the Kilian Index and Nord Pool electricity prices.

3.2 Methodology

The first step of the methodological strategy will be to analyze what might be the influence of carbon prices on those variables. To assess the response of a shock of the carbon price to emission trends and the economic, financial, energy, and climate variables, Impulse-Response Functions (IRF) will be modeled. IRFs are helpful to investigate interactions in a vector autoregressive (VAR) framework. However, within VAR models, it might be often challenging to assess which shocks are relevant (Lütkepohl, 2008). To overcome this issue, vector autoregressive models would usually be orthogonalized (i.e., Structural Vector Autoregressive models). In the case of this analysis, as carbon price is also influenced by variables such as emissions and commodity prices, the shock cannot be orthogonalized. To account for this, the computation of the IRF follows a generalized approach (Pesaran & Shin, 1998) to relax some further limitations, not considering the

[5] For this work it has been decided to use closing prices.

[6] from April 2015, Netherlands Title Transfer Facility (TTF); April 2010 to March 2015, average import border price and a spot price component, including UK; during June 2000—March 2010 prices exclude UK.

Table 2 Multiple stationarity tests

	Variable	box.pvalue	adf.pvalue	kpss.pvalue	box	adf	kpss
1	Kilian Index	0	0.155	0.010	TRUE	FALSE	FALSE
2	Brent	0	0.518	0.010	TRUE	FALSE	FALSE
3	CO_2	0	0.010	0.029	TRUE	TRUE	FALSE
4	EUA	0	0.704	0.010	TRUE	FALSE	FALSE
5	Max Temperature	0	0.010	0.100	TRUE	TRUE	TRUE
6	Tot Rainfall	0.011	0.010	0.100	TRUE	TRUE	TRUE
7	Min Temperature	0	0.010	0.100	TRUE	TRUE	TRUE
8	Wind Speed 10mt	0	0.010	0.100	TRUE	TRUE	TRUE
9	Dutch TTF	0	0.594	0.010	TRUE	FALSE	FALSE
10	North Pool Electricity	0	0.212	0.018	TRUE	FALSE	FALSE
11	STOXX50E	0	0.010	0.010	TRUE	TRUE	FALSE
12	Rotterdam Coal Futures	0	0.014	0.012	TRUE	TRUE	FALSE

Table 3 Correlation matrix

	Kilian Index	Brent	CO_2	EUA	Max Temperature	Tot Rainfall	Min Temperature	Wind Speed 10mt	Dutch TTF	North Pool Electricity	STOXX50e	Rotterdam Coal Futures
Kilian Index	1											
Brent	0.357	1										
CO_2	0.242	0.273	1									
EUA	0.660	0.145	0.118	1								
Max Temperature	0.054	0.112	-0.717	0.006	1							
Tot Rainfall	0.019	-0.029	0.131	-0.114	-0.111	1						
Min Temperature	0.070	0.075	-0.684	-0.008	0.962	-0.014	1					
Wind Speed 10mt	-0.033	-0.080	0.645	0.031	-0.872	0.200	-0.828	1				
Dutch TTF	0.352	0.712	0.553	0.240	-0.079	0.071	-0.078	0.094	1			
North Pool Electricity	0.380	0.271	0.409	0.554	-0.289	-0.021	-0.331	0.153	0.344	1		
STOXX50E	0.096	-0.232	-0.132	0.161	-0.025	-0.123	-0.006	0.103	-0.399	-0.153	1	
Rotterdam Coal Futures	0.702	0.626	0.352	0.613	0.040	-0.047	0.041	-0.014	0.554	0.487	0.075	1

order of the variables. IRF maps out the type of influence (positive or negative) a shock of carbon prices might exert on the other variables. As the next step, the Forecast Error Variance Decomposition (FEVD) of the model's single variables will be analyzed to assess how much of the variance of a particular variable might be explained by the variance of carbon prices. Ideally, the higher the contribution of other variables, the more integrated the system is and the more robust the results and trends of the IRF (Lütkepohl, 2005). Thus, in this analysis, the higher the contribution of carbon price in the variance of the other variables, the more robust the results from the IRF are. In line with the previous analysis, the computation of FEVD follows the approach of Pesaran and Shin (1998).

3.2.1 HVAR

As for the vector autoregressive model, the methodological strategy considers the high dimensional context of the analysis. For this reason, the Hierarchical Vector Autoregressive Model (HVAR) will be employed to address this high-dimensional context. This methodology was first introduced by W. B. Nicholson et al. (2020) as a more suitable solution for forecasting exercises in high dimensional contexts concerning other approaches to reduce the dimensionality of time series (e.g., correlation analysis, factor models, Bayesian models, scalar component models, independent component analysis, dynamic orthogonal component analysis). Starting from the matrix representation of a $VAR(p)_k$ model where $\{y_t \in R_k\}_{t=1}^{T}$ denote a k-dimensional vector time series of length T[7]:

$$Y = v1^{\intercal} + \Phi Z + U \tag{1}$$

where Φ controls the dynamic dependent of the *ith* component of y_t on the *jth* component of y_{t-1}. In the classical low-dimensional framework in which $T > kp$ one may use the least square procedure to minimize the VAR model as such:

$$\|Y - v1^{\intercal} > -\Phi Z\|_2^2 \tag{2}$$

where $\|A\|_2$ denotes the Frobenius norm of the matrix A, that is the Euclidean norm of $vec(A)$. Estimating the parameters of Eq. 2 would be difficult unless T is sufficiently large.[8] The traditional estimation cannot estimate VAR in high dimensions as the number of variables increases, and the parameter spaces grow quadratically, leading to a loss of degrees of freedom (Bagheri & Ebrahimi, 2020). One way to treat moderate to small T is to make structural assumptions on the parameter space. Some authors conceived lasso-based VAR under the assumption that the matrix of the coefficient in a high dimensional context is sparse (Song & Bickel, 2011). HVAR pertains to this family of models as it encodes lag order selection into a convex regularization that simultaneously addresses dimensionality and lag order selection. However, unlike Bayesian models and lasso-based models, it provides interpretable insights into the contribution of each time series to the forecasting exercise. While aiming at interpretability, HVAR

[7] For the notation see Appendix 1.

[8] Indeed, when $T > kp$ but $kp/T \approx 1$, estimation by least squares becomes imprecise.

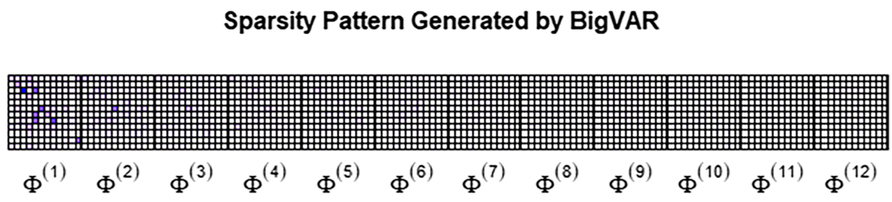

Fig. 1 Sparsity matrix of elementwise HVAR

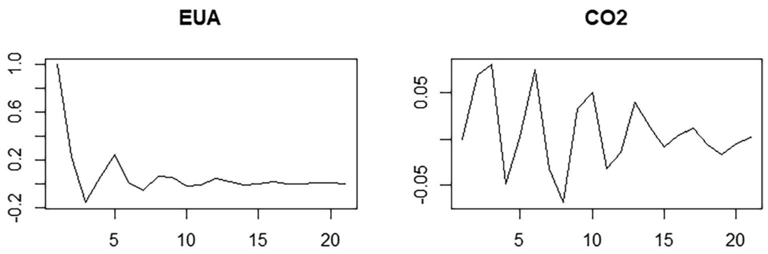

Fig. 2 Impulse-response function CO_2 emissions

introduces maximization in lag order selection dealing with increasing maximal order. In other models, forecasting performances tend to degrade as lag order increases. Furthermore, for large (even medium) k, the matrix of the coefficients is considered sparse. The same is valid for the data-generating process (DGP) (Davis et al., 2012). Song and Bickel (2011) have decided to implement convex penalty mechanisms (e.g., Lasso and Group Lasso). In this framework, HLag builds on hierarchical group lasso modeling, providing a structure to the sparse matrix with different degrees of flexibility (i.e., Componentwise, Own-Other, Elementwise). Each row of the equation of the VAR might truncate at a given lag order (e.g., Componentwise) or allow the lag order of the single series to truncate at a different order with respect to the other series (i.e., Own-other). The lag structure might also allow each series component to have its own lag order (e.g., Elementwise). While other approaches (i.e., information criteria) provide a universal lag order, Hlag allows lag to vary across marginal models. For the sake of this work, the Elementwise HLag structure has been chosen as the more flexible and better performing in multiple scenarios, also concerning other lasso-based methods, as seen in W. B. Nicholson et al. (2020). Following the notation in Eq. 1, being L a kxk matrix of elementwise coefficient lags

$$L_{ij} = max\left\{\ell \, : \, \phi_{ij}^{(\ell)} \neq 0\right\} \tag{3}$$

as the smallest maximal lag structure such that $\Phi_{ij}^{(\ell)} = 0, \ell = 0, \ldots, p$ for the model considered. For other structures, Elementwise HLag allows all the elements within L to have no stipulated relationships. HVAR performances have been tested for macroeconomic and financial forecasting W. B. Nicholson et al. (2020). Aside from mere forecasting, Bagheri and Ebrahimi (2020) employ this methodology to investigate the interconnectedness of financial stock indexes. To the best of the author's

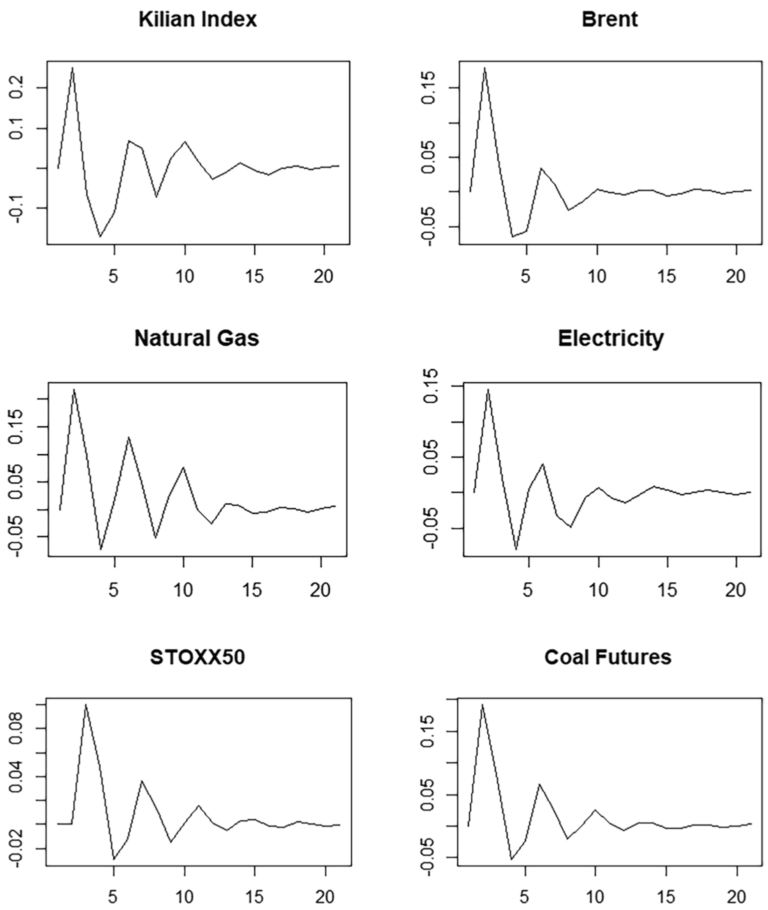

Fig. 3 Impulse-response economic, financial, commodities price

knowledge, this will be the first attempt to employ Hierarchical Vector Autoregressive models for variable-to-variable analysis (i.e., impulse response) in environmental macroeconomics.

4 Results

Despite some exceptions, all the tests run (e.g., Augmented Dickey-Fuller, KPSS, Box-Ljiung) show the series present non-stationarity either in trends or in drift (Table 2). Therefore, the series will be analyzed in their first differences in the following steps.

Since there is no consistent way to choose the maximum lag order that applies to HVAR estimation, W. Nicholson et al. (2017) suggest that the parameter p will be set according to the frequency of the time series considered (e.g., 12 for monthly series). Once the coefficient is estimated, cross-validation will be performed by dividing the dataset into three parts: T/3 and 2 T/3, respectively. Figure 1 shows the sparsity matrix of the coefficients as the result of the model specification with 12 maximum lags. Furthermore, the matrix shows that the model does not consider any ex-ante relationship between data (e.g., Elementwise). From here, it is possible to appreciate how the coefficients of the diagonals tend to weigh more on estimation than off-diagonal. In other words, the coefficients of the lagged variables tend to influence the estimation more than the single marginal equations.

As for the optimization procedure, the chart in Figure 5 in Appendix 2 shows a parabolic shape for the penalization term λ. Figures 2 and 3 show the response of the first differences in carbon dioxide emission, the Kilian Index, commodity prices, and the STOXX50 and relevant system variables to a shock on EUA. Figures 2 and 3 show the specification of the model considering temperatures (min, max), wind speed at 10 mt, and total rainfall. Focusing on the response of carbon dioxide emissions, it is possible to appreciate how the shock generates a cyclical trend for future emissions, which progressively converge to 0 after $t=20$.

As for the variables considered in the model, Fig. 3 models IRF for commodity prices, production, and financial indexes; EUA appears to exert a decrease after an increase for the Kilian Index and specific commodity prices (e.g., Brent, Natural Gas) that converge to 0 after $t=10$. As for the STOXX50 index and Nord Pool electricity, a carbon price shock appears to exert an intense response, at least shortly.

Decomposition (FEVD) is depicted in Fig. 4, respectively, to 1, 5, 10, and 20 steps ahead (in Appendix 3, Table 4 summarizes the results of the FEVD). As shown in Fig. 4, most of the variance of the single variables is explained by their own variance. For the variable of interest (e.g., CO_2), other influences mostly come from the climate/weather variables and commodity prices. Kilian Index and Natural Gas and Coal prices explain the carbon dioxide variance between 10%-15% of the carbon dioxide variance. As for the influence of EUA price, despite being relatively low (6%-7%), the value slightly increases over time. The most significant influence of EUA price ranges between 4%-5% for (max) temperature, natural gas price, and Kilian Index. On the other hand, much of the external variance of carbon price is related to commodity prices and temperatures (min, max).

5 Discussion

For the hypothesis of this work, the influence of carbon price over carbon emissions and economic, financial, and climate variables is relatively weak. In the case of CO_2, other factors directly influence emissions. As for the other economic, financial, and energy variables, it might be related to the fact that the carbon market seems to be a net receiver of shocks when related to other relevant markets such as commodities and electricity (Tan et al., 2020). From Fig. 3, it is possible to see that a shock increases and then decreases carbon prices before $t=5$. In $t=5$, there is another spike, and the response converges to 0 afterward. The results of the IRF show a cyclical response of CO_2 to a shock. The response, though, is more persistent with respect to the other variables. This can be related to the response of the other variables to the shock of EUA prices. The effect of the shock

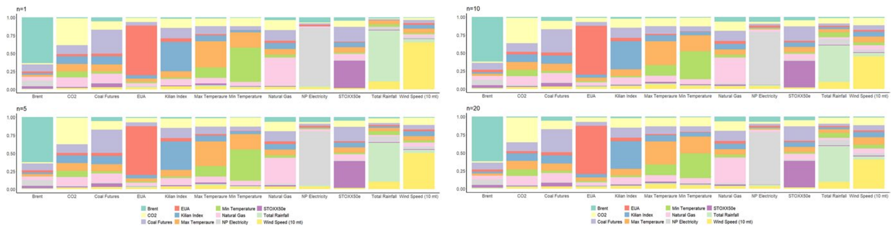

Fig. 4 Forecast error variance decomposition

on the economic and financial variables is transmitted in turn to the CO_2. As for the other variables, the results of the IRF in Fig. 3 show a positive response before t = 5, followed by a negative. The series converges to 0 after t = 10. The response of the Killian Index might be related to the behavior of fuel prices. Before t = 5, the fuel price increase is transmitted to the industrial production that falls after t = 5. For the commodity market, the response aligns with the hypothesis that increased carbon prices generate higher fuel prices (Ma et al., 2021). The price of fuels increases due to the increase in carbon price. The subsequent negative response might be related to fuel switching. After a period of price increase, buyers may use the cheapest fuel, thus decreasing prices. The STOXX50 index appears to have a positive relationship with EUA prices in the short term. This aligns with previous studies on the relationship between carbon prices and STOXXX market returns (Mischiller et al., 2023). There is a subsequent negative response of the index probably related to the higher carbon cost of those enterprises that have to buy emission allowances.

However, according to the FEVD, EUA prices explain only 3% of the variance in carbon emissions. As for the influence on other variables, carbon price explains 5% of the variation of the Kilian Index and from 3 to 4% of fuel prices. External factors explaining CO_2 variation are industrial production (10%), natural gas (13%), and coal prices (12%). Industrial production and commodity prices directly influence the levels of CO_2: higher industrial production increases emissions from the industrial sector. On the other hand, lower prices increase the consumption of fossil fuels in the energy mix and, in turn, atmospheric emissions (Declercq et al., 2011; Dong et al., 2019; Zeng et al., 2021). Figure 4 shows no relationship between the carbon market and the financial market. As mentioned, this could be related to the type of enterprises considered in the index and whether they buy/sell allowances. The STOXX50 index includes firms in different sectors: finance, power sectors, textile, food and beverage, bank, and automotive. Some, but not all, of them are included in the scheme. This could explain the almost non-existent influence of carbon price on the index. Climate variables appear to be not directly influenced by carbon prices. Maximum temperatures influence the carbon price in line with other findings in the literature where absolute deviation from the average temperatures is significant in explaining carbon prices (Batten et al., 2021; Feng et al., 2011). As for the relationship between wind characteristics (e.g., speed, direction) and carbon price, the results highlighted that there might be some connection. The variance of wind speed explains around 3% of the EUA variance. However, providing further insight into this relationship with this methodology is impossible. Wind characteristics and carbon prices might be connected through renewable sources.

Thus, considering some proxy of renewable energy sources (e.g., wind power) in the model should lead to more marked results. Besides the results of this analysis, one other reason might be related to the presence of national policies that may overlap with the EU ETS. Most of the sectors within the EU ETS are heavily regulated at the national level. The national policy may interfere with the connection between the carbon price and emissions. Furthermore, as shown by the IRFs, carbon price affects other variables (e.g., industrial production, energy) that, in turn, affect CO_2. However, delving more into this kind of analysis goes beyond the scope of this work.

6 Conclusions

This work tries to provide ulterior insights on the effect of the emission trading scheme at the EU level, considering the broader system (environmental, economic, financial). The EU ETS represents the cornerstone of the EU climate policy. However, since its introduction in early 2005, carbon prices have not reached a (high) sufficient level. The main strands of the literature have focused on the determinants of carbon prices. Studies on the effectiveness of carbon prices have been mainly conducted at micro level, investigating the effect ETS on emission and the economic performances of firms. In this framework, this work aims to investigate the effectiveness of carbon price through testing the response of environmental, economic, financial, energy and climate variables to a shock of EUA prices for the EU. Unlike other studies, this work includes many variables of different nature to cover the multiple dimensions of the relationship between carbon price and the economic-environmental system. It employs time series econometrics coupled with lasso-based regularization to provide new insights into the effectiveness and integration of the EU ETS within the socio-economic-environmental system. This provides interpretable estimates that have been used to model IR functions and FEVD analysis. The IR functions highlighted how a shock in carbon price will generate a cyclical response to CO_2. This cyclical response appears to be persistent over time. This persistent cycle might be the effect of the other variables responding to the carbon price shock. This proves a mediated effect of carbon prices on CO_2, which is not possible to capture with this kind of analysis fully. According to the IR estimation, the other variables also show a cyclical response. However, this response is less persistent and rapidly converges to zero after a few years.

After experiencing an increase, industrial production decreases due to the increase in fuel prices. Commodities respond to an increase in fuel prices through fuel switching. If, in the short term, a shock in carbon prices is associated with a higher value of the STOXX50 index, the higher carbon cost for some of the enterprises in the index generates a decrease afterward. However, from the FEVD, it was possible to assess that the effective influence of carbon prices on those variables is still weak. There appear to be other factors that exert a stronger influence on carbon dioxide than EUA prices (e.g., temperatures, industrial performances, natural gas, coal). Results align with the preliminary analyses (e.g., correlation matrix) and the literature pointing out the influence of carbon prices on industrial performances, commodities, and (maximum) temperatures. These findings provide ulterior insights to policymakers for better considering possible sources of carbon price shocks (e.g., overlapping policies) and tailoring existing adjustment mechanisms (e.g., Market Stability Reserve) for the stability of the European Emission Trading Scheme. However, even when considering multiple factors, the influence of carbon prices on the EU appears weak. Further limitations might be related to the interpretability of the results, especially when considering more variables in the algorithm. Future work might consider Phase IV of the ETS, where the Market Stability Reserve is fully implemented. Research should also look at the behavior of prices during the COVID-19 pandemic, where higher prices were associated with a lower volume of transactions. Despite the well-established influence on commodity markets, the almost non-existent influence of carbon prices on finance *strictu* sensu could be deemed an ulterior hurdle to channeling funds toward sustainable investments. Thus, a more active dialogue between national and EU policymakers should lead to a comprehensive policy mix, avoiding overlapping aims. Even though the EUA has been included as a financial instrument by the recent EU financial directive (MiFID2), financial players do not consider carbon allowances enough. From this perspective, the vast process of reform affecting the financial sector (e.g., Taxonomy) should be designed considering the comprehensive array of policies from multiple aspects.

Appendix 1

$$Y = v1^{\mathsf{T}} + \Phi Z + U \tag{4}$$

$$\begin{gathered} Y = \left[y_1 \dots \mathrm{y}_T\right](k\ x\ T);\ \mathrm{Z} = \left[z_1 \dots \mathrm{z}_T\right](kp\ x\ 1); \\ \mathrm{z} = \left[y^{\mathsf{T}}{}_{t-1} \dots \mathrm{y}^{\mathsf{T}}{}_{t-p}\right](kp\ x\ T);\ \mathrm{U} = \left[u_1 \dots u_T\right](k\ x\ T); \\ 1 = [1 \dots 1]^{\mathsf{T}}(T\ x\ 1);\Phi = \left[\Phi^{(1)} \dots \Phi^{(p)}\right](k\ x\ kp) \end{gathered}$$

Appendix 2

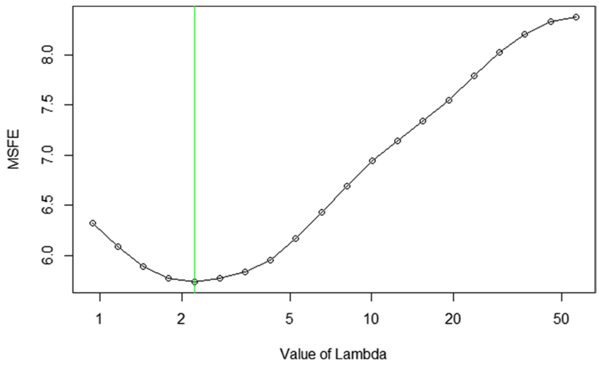

Fig. 5 Lamba plot

Appendix 3

Table 4 Results of the Forecast Error Variance Decomposition for the variables included in the HVAR estimation

Variables	Kilian Index	Brent	CO_2	EUA	Max Temperatures	Tot Rainfall	Min Temperatures	Wind Speed 10mt	Dutch TTF	North Pool Electricity	STOXX50e	Rotterdam Coal Futures
Horizon 1												
Kilian Index	0.41	0.02	0.13	0.05	0.09	0.00	0.02	0.04	0.09	0.00	0.01	0.15
Brent	0.02	0.64	0.02	0.02	0.03	0.01	0.00	0.00	0.05	0.08	0.04	0.10
CO_2	0.11	0.01	0.38	0.03	0.10	0.00	0.08	0.02	0.13	0.00	0.01	0.12
EUA	0.04	0.00	0.06	0.69	0.05	0.01	0.02	0.03	0.04	0.01	0.00	0.05
Max Temperatures	0.08	0.02	0.11	0.02	0.37	0.02	0.14	0.04	0.08	0.00	0.02	0.11
Tot Rainfall	0.00	0.02	0.01	0.00	0.05	0.71	0.04	0.11	0.01	0.03	0.01	0.01
Min Temperatures	0.03	0.01	0.12	0.00	0.21	0.01	0.48	0.03	0.05	0.01	0.01	0.05
Wind Speed 10mt	0.05	0.00	0.03	0.03	0.06	0.05	0.02	0.65	0.04	0.02	0.01	0.04
Dutch TTF	0.08	0.04	0.14	0.03	0.08	0.00	0.04	0.03	0.39	0.01	0.01	0.15
North Pool Electricity	0.00	0.07	0.01	0.02	0.00	0.02	0.00	0.03	0.02	0.81	0.00	0.02
STOXX50e	0.07	0.05	0.08	0.01	0.07	0.00	0.02	0.02	0.08	0.01	0.38	0.21
Rotterdam Coal Futures	0.11	0.05	0.12	0.04	0.10	0.00	0.03	0.03	0.13	0.01	0.05	0.33
Horizon 5												
Kilian Index	0.40	0.02	0.13	0.05	0.09	0.00	0.02	0.04	0.09	0.01	0.01	0.14
Brent	0.02	0.62	0.02	0.03	0.03	0.01	0.00	0.00	0.05	0.08	0.04	0.10
CO_2	0.11	0.01	0.36	0.03	0.11	0.00	0.09	0.02	0.13	0.01	0.01	0.12
EUA	0.05	0.01	0.06	0.68	0.05	0.01	0.02	0.03	0.04	0.01	0.01	0.05
Max Temperatures	0.08	0.01	0.11	0.02	0.34	0.02	0.14	0.05	0.08	0.00	0.02	0.11
Tot Rainfall	0.02	0.02	0.06	0.02	0.04	0.54	0.05	0.11	0.02	0.08	0.01	0.03
Min Temperatures	0.04	0.01	0.12	0.01	0.21	0.01	0.44	0.03	0.06	0.01	0.01	0.06

Table 4 (continued)

Variables	Kilian Index	Brent	CO_2	EUA	Max Temperatures	Tot Rainfall	Min Temperatures	Wind Speed 10mt	Dutch TTF	North Pool Electricity	STOXX50e	Rotterdam Coal Futures
Horizon 1												
Wind Speed 10mt	0.07	0.01	0.10	0.02	0.06	0.04	0.03	0.50	0.06	0.04	0.01	0.06
Dutch TTF	0.08	0.06	0.13	0.04	0.08	0.00	0.04	0.03	0.36	0.02	0.02	0.14
North Pool Electricity	0.01	0.07	0.02	0.02	0.01	0.02	0.01	0.04	0.03	0.75	0.00	0.03
STOXX50e	0.07	0.05	0.08	0.02	0.07	0.00	0.02	0.02	0.08	0.01	0.37	0.20
Rotterdam Coal Futures	0.11	0.05	0.12	0.04	0.10	0.00	0.03	0.03	0.12	0.01	0.05	0.32
Horizon 10												
Kilian Index	0.39	0.02	0.13	0.05	0.09	0.01	0.02	0.04	0.09	0.01	0.01	0.14
Brent	0.02	0.62	0.02	0.03	0.03	0.01	0.00	0.00	0.05	0.08	0.04	0.10
CO_2	0.11	0.01	0.35	0.03	0.11	0.00	0.09	0.02	0.12	0.01	0.01	0.12
EUA	0.04	0.01	0.06	0.68	0.05	0.01	0.02	0.03	0.04	0.01	0.01	0.05
Max Temperatures	0.08	0.02	0.11	0.02	0.33	0.02	0.15	0.06	0.08	0.00	0.02	0.11
Tot Rainfall	0.03	0.02	0.08	0.02	0.05	0.51	0.07	0.10	0.03	0.08	0.01	0.03
Min Temperatures	0.05	0.01	0.12	0.01	0.22	0.01	0.39	0.04	0.06	0.01	0.01	0.07
Wind Speed 10mt	0.07	0.01	0.10	0.02	0.08	0.05	0.04	0.45	0.06	0.04	0.01	0.07
Dutch TTF	0.08	0.06	0.13	0.04	0.08	0.01	0.04	0.04	0.36	0.02	0.02	0.14
North Pool Electricity	0.01	0.07	0.03	0.02	0.01	0.02	0.01	0.04	0.03	0.73	0.00	0.03
STOXX50e	0.07	0.05	0.08	0.02	0.07	0.00	0.02	0.02	0.08	0.01	0.37	0.20
Rotterdam Coal Futures	0.11	0.05	0.12	0.04	0.10	0.00	0.03	0.03	0.12	0.01	0.05	0.32
Horizon 20												
Kilian Index	0.38	0.02	0.13	0.05	0.09	0.01	0.02	0.04	0.09	0.01	0.01	0.14

Table 4 (continued)

Horizon 1												
Variables	Kilian Index	Brent	CO_2	EUA	Max Temperatures	Tot Rainfall	Min Temperatures	Wind Speed 10mt	Dutch TTF	North Pool Electricity	STOXX50e	Rotterdam Coal Futures
Brent	0.02	0.62	0.02	0.03	0.03	0.01	0.00	0.00	0.05	0.08	0.04	0.10
CO_2	0.11	0.01	0.34	0.03	0.12	0.00	0.09	0.03	0.12	0.01	0.01	0.12
EUA	0.05	0.01	0.06	0.67	0.05	0.01	0.02	0.03	0.04	0.01	0.01	0.05
Max Temperatures	0.09	0.02	0.12	0.02	0.32	0.01	0.15	0.06	0.08	0.01	0.02	0.11
Tot Rainfall	0.03	0.02	0.08	0.02	0.05	0.50	0.07	0.10	0.03	0.08	0.01	0.03
Min Temperatures	0.06	0.01	0.12	0.01	0.23	0.01	0.34	0.05	0.07	0.01	0.01	0.08
Wind Speed 10mt	0.07	0.01	0.11	0.02	0.10	0.05	0.05	0.41	0.07	0.03	0.01	0.07
Dutch TTF	0.08	0.06	0.13	0.04	0.08	0.01	0.04	0.04	0.35	0.02	0.02	0.14
North Pool Electricity	0.01	0.07	0.03	0.02	0.01	0.02	0.01	0.04	0.03	0.73	0.00	0.03
STOXX50e	0.07	0.05	0.08	0.02	0.07	0.00	0.02	0.02	0.08	0.01	0.37	0.20
Rotterdam Coal Futures	0.11	0.05	0.12	0.04	0.10	0.00	0.03	0.03	0.12	0.01	0.05	0.32

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