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

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Abstract

The following work will provide further insights into the influence of European Emission Allowance (EUA) prices on carbon dioxide trends and relevant variables of the economic-financial climate-environmental system considering a large set of time series. The methodological approach will employ Hierarchical Vector Autoregression by W. B. Nicholson et al. (2020) deal with a high-dimensional context. Results of the two specifications highlighted how CO2 appears to be more influenced by commodity prices, climate variables, along with past industrial performances. Furthermore, a shock of carbon prices could potentially exert significant turbulence on the carbon dioxide series, fading in intensity as time goes by. Overall, despite some instances (e.g., CO2), there appears to be a straightforward (negative) effect on the influence of carbon prices on the system. However, further analyses identified how the external contribution to the variance appears to be quite limited for the variable of interest (i.e., carbon price) and the others. As the cornerstone of the EU climate policy, this work sheds light on the influence the EU ETS exerts on a set of multidimensional variables, considering the possible sources of shocks and implementing adjustment mechanisms for EUA prices.

Keywords: EU ETS; emission trading; Hierarchical VAR; Impulse-Response

JEL Code: Q52, Q58, C54

1. Introduction

Carbon and carbon dioxide are fundamental for humans and the Planet. However, the last decade has witnessed a surprising amount of human-made carbon dioxide emissions in the atmosphere with irreversible consequences for future climate patterns. This occurrence has altered the equilibrium of temperature and, in turn, climate pathways. Thus, if not promptly addressed, adaptation costs to climate change will become unsustainable for humanity. The international community calls for a joint pledge of nations to tackle climate change lowering CO_2 emitted due to human activities. After the Kyoto Protocol was adopted and entered into force in 2005, most industrialized nations pledged to reduce their GHG primarily via three market-based mechanisms. Emission Trading (ET), Clean Development Mechanism (CDM), and Joint Implementation are the tools agreed upon by the Conference of Parties (COP-3) to try to curb emissions within the objectives of the Protocol. Since then, the carbon market has become one concrete policy option for States to comply with Kyoto Protocol obligations. Carbon is now *de-facto* a commodity, and the number of carbon markets worldwide has grown in the last couple of years. World Bank (2020) argue that most of the trading schemes at the international level only cover heavily polluting sectors. According to the latest account by World Bank (2021), the 64 emission trading schemes worldwide cover more than 20% of the global GHG emissions generation. Charging a price on CO_2 emissions might give a consistent shift to the ongoing course of action. Pricing carbon will provide a reward for implementing low-carbon production processes (High-level Commission on Carbon Prices, 2017). Especially for developing economies, a carbon price might prevent development from being locked into a carbon-intensive path (Hourcade and Shukla, 2013). However, a sensible difference exists between the optimal theoretical framework and the practical implementation of a carbon price scheme (High-level Commission on Carbon Prices 2017).

Even though single initiatives of the Member States, the European Union, in 2005 launched the so-called European Emission Trading Scheme (EU ETS) Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 Establishing a Scheme for Greenhouse Gas Emission Allowance Trading within the Community and Amending Council Directive 96/61/EC. So far, the mechanism has been functioning for more than a decade, providing a price primarily to CO_2 emissions for specific categories of enterprises (see Annex I, Directive 2003/87/EC) within the European territory. As such, the EU ETS has attracted the interest of policymakers and in the academic world (Convery 2008; C.-J. Ji et al., 2019). Several streams of research, (Chevallier 2011a; Convery 2008; C.-J. Ji et al. 2019), have tried to disentangle drawbacks, strengths, determinants of the European Union Allowance (EUA) price. Price stability has been a growing concern for European policymakers (Ellerman and Buchner, 2008). Since its first steps, EUA prices have not reached a stable trend over the years, reaching zero transactions at the end of Phase I. An appropriate account of the social costs of carbon is still an open issue and a perceived hurdle to achieving a societal transition towards sustainability (Pearce 2003). Estimates of a carbon price in the 34 IPCC scenarios (430-480 ppm of CO2 by 2100), as computed by IPCC (2014); Tvinnereim and Mehling (2018), range from US$37 to US$67 per tonne of CO_2 in 2020, whereas in 2050 would be US$127-US$305. However, if carbon pricing could generate revenue flows reducing the overall tax burden, more flexible pricing mechanisms could likely imply less adverse effects on competitiveness (OECD, 2016b).

Very few contributions have endeavoured to assess the effect of the EU ETS' carbon price behaviour on GHGs emission generation. Grosjean et al. (2016) proved exogenous shocks undermining price stability might come from different sources (e.g., economic recession, overlapping policies, a large influx of Certified Emission Reduction/Emission Reduction Units). Furthermore, while adjustment mechanisms (e.g., MSR) have been implemented, Azarova and Mier (2021) argued that further investigations of their effects favouring GHGs abatement would deliver a more extensive understanding of the functioning of those mechanisms. 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 the 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).

As curbing emissions is the foremost objective of the entire mechanism, the present work will test the effects of shocks on EUA prices that might affect carbon emission and a set of relevant variables. Ideally, a positive shock on EUA price will negatively impact emission generation. This work will test this hypothesis adopting a vector autoregressive (VAR) framework considering a large set of time series from economic (i.e., industrial production), to energy (natural gas, crude oil, electricity), to financial, to climate/weather (temperatures, rainfall patterns, wind speed). In a much broader perspective, the paper will analyse the current state of the interplay among carbon price mechanisms and other relevant dimensions (e.g., industry, energy, finance) via assessing their response to a shock on EUA prices considering the broader system (e.g., including climate, environmental dimension) (Schusser and Jaraitė 2018). In this framework, the Hierarchical Vector Autoregressive (HVAR) model by W. B. Nicholson et al. (2020) will provide a sound methodological approach to this high-dimensional context. Building on the assumption the matrix of the lagged coefficient is sparse, HVAR employs a lasso-based structure with various degrees of flexibility in the hypothetical structure this matrix should have. Besides forecasting, the methodology has been used in Bagheri and Ebrahimi (2020), assessing the connectedness between financial markets and commodity markets. Indeed, via employing this methodology, this will be modeling the system's response to a shock of CO_2 prices in a more flexible context capable of better accounting for the behaviours of each dimension (e.g., economic, environmental, climatic) (Chevallier 2011b). W. B. Nicholson et al. (2020) proved HVAR delivers better forecast performances with respect to other models fitted for high-dimensional time series (when k increases). Concerning other approaches, HVAR is better suited to deal with multi-dimensional variables because it takes into account the behavior of the single time series. Impulse-Response functions will be derived from the estimates of the HVAR. From this, it will be possible to deliver a variable-to-variable analysis modelling the response of relevant variables to a shock on carbon prices. Beside IRF analysis, Forecast Error Variance Decomposition analysis will investigate on the influence of EUA prices on the set of variables. Results highlighted how EUA prices still play a relatively weak role in influencing the other variables of the system. Thus, the contribution of this work to the literature is manifold. This paper can be included within the growing research endeavors trying to frame machine learning techniques within economic analysis and policy evaluation. In some cases, when dealing with high frequency or high dimensionality of the data, machine learning techniques appear to fare better with respect to standard econometrics (Athey, 2017; Athey & Imbens, 2017; Varian, 2014). Indeed, this paper couples machine learning with standard time series econometrics to deal with high dimensionality of data. In light of the research question of this work, HVAR represents a more appropriate methodology to assess how the behavior of carbon price at the EU level might affect the economic, financial, environmental, and climatic dimensions. This is much more valid when dealing with a high-dimensional context and in presence of variables of different nature (environmental, economic, financial, climatic). On the other hand, the work will also feed the literature on the effectiveness of carbon prices with respect to GHGs emissions. While some instances have analysed focused on a micro (e.g., firm level) dimension, this work will provide a novel empirical approach for macroeconomic analysis considering the EU as a whole. VAR-based methodology has already been used until recently to carbon prices analysis (Känzig, 2021). Furthermore, this paper will be one of the first applications of HVAR methodology in (macro)economic analysis for climate policy evaluation. To policymakers, this work might provide useful insights as to the current role of carbon prices in the socio-environmental system accounting for the different nature of the variables. The work proceeds with a brief overview of the theoretical and institutional underpinnings of the EU ETS, highlighting the main criticalities. Further, a detailed description of the data employed and the methodology followed by estimating the Impulse-Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). The last two sections will provide comments and discussions on the results with conclusions and implications for policymakers.

2. EU ETS- Literature Review

From a legislative point of view, the EU ETS was instituted with Directive 2003/87/EC of the European Parliament and of the Council of 13 October, 2003 Establishing a Scheme for Greenhouse Gas Emission Allowance Trading within the Community and Amending Council Directive 96/61/EC (Text with EEA Relevance). Currently, it operates in 31 Countries, 27 EU Countries, plus Iceland, Norway, Liechtenstein, and the United Kingdom. It is designed to cover 45% of the total EU-wide GHG emissions. Right now, it accounts for 11,000 heavy energy-using installations all over Europe. Over the three phases, the system has highlighted some criticalities that appear to be expected in emission trading design. Indeed, Chevallier (2011a); Asian Development Bank (2015); Borghesi et al. (2016); Perino and Willner (2016); Brouwers et al. (2016);Bruninx and Ovaere (2022) highlighted all those relevant issues that could be reduced to institutional factors (e.g., lack of long-term political commitment, adjustment mechanisms) and agents' expectations (e.g., Australian Carbon Mechanism). In its early stages of implementation, the system has also experienced frauds (e.g., carousel fraud, Black Stone). One other point is related to price behaviour that has not reached a stable trend scheme[1] with a tendency to allocate more permits to favour their domestic industrial enterprises during the first phases. As for policy commitment, Lecuyer and Quirion (2013); Schusser and Jaraitė (2018); Shahnazari et al. (2017) have proved empirically that other instruments might be complementary to carbon price at the local level, especially in the power sector. Expectations are mostly related to risks and uncertainty at the policy level (energy efficiency, technology) and the market level (commodity prices) (Blyth and Bunn, 2011). One of the latest, the Market Stability Reserve, conceived a mechanism that creates a corridor for the number of allowances that can be traded in the market.

Aside from the overall faring of the system, researchers have been striving to find determinants of European Union Allowances (EUA). Alberola et al. (2008); Creti et al. (2012); Aatola et al. (2013); Koch et al. (2014) found that EUA prices are influenced by weather (temperature, extreme weather events) indicators, other commodity prices (i.e., oil, gas), industrial productivity, financial markets[2] (e.g., commodities). Q. Ji et al. (2019); Oberndorfer (2009); Soliman and Nasir (2019); Zhu et al. (2018) have identified the influence of commodity markets (i.e., coal, gas, oil, electricity) and other carbon markets. Hitzemann et al. (2015); Eugenia Sanin et al. (2015) investigated the effects of specific announcements on EUA price volatility. Despite the need to consider the nature of CO_2 behaviour, as stated by Chevallier (2011b), most studies have focused on the functioning principles of the scheme.

Research efforts have also tried to disentangle the effects of emission trading on diverse aspects. Adopting a diff-in-diffs approach, Marin et al. (2018) and Löschel et al. (2019) analyzed the impact of EU ETS on the economic performance of Italian and German enterprises, respectively. Teixidó et al. (2019) reviewed the

[1] for a deeper insight on EUAs price behaviour see https://www.sendeco2.com/it/prezzi-co2 or https://www.eex.com/en/market-data/environmental-markets/spot-market/european-emission-allowances

[2] 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.

empirical literature on the effectiveness of emission trading in fostering a low-carbon technological transition. Naegele and Zaklan (2019); Koch and Basse Mama (2019) dealt with carbon and investment leakage potentially caused by the scheme. In the context of the UK, Abrell et al., (2022) coupled machine learning techniques with economic theory to assess the effect of UK CPS on emissions. Gugler et al., (2021) compared the results of EUA carbon price and emission reduction in Germany and UK CPS. They found the higher prices for UK emissions led to a more significant reduction.

2.1 Effectiveness of the policy

Despite the effective decreasing trend in CO_2 over the last decade, Brink and Vollebergh (2020) notice it is pretty hard to trace the direct effect of the EU ETS considering the multiple factors involved. The amount of emission reduction might also be influenced by unilateral policy interventions (Perino et al. 2019). However, McGuinness and Ellerman (2008); Ellerman and Buchner (2008); Ellerman and Feilhauer (2008); Anderson and Di Maria (2011); Martin et al. (2016); Dechezleprêtre et al. (2018) highlighted how EU ETS has been effective in decreasing emissions in different Phases of the scheme using country-level data. All the studies highlighted a contribution of EU ETS in abating emissions, despite the difficulty of measuring the counterfactual. However, possible exogenous shocks can undermine the stability pathway of prices with consequences for reaching the targets (Grosjean et al. 2016). Aside from shocks deriving out of economic urmoil, Lecuyer and Quirion (2013); Shahnazari et al. (2017), Perino et al. (2019), Bruninx and Ovaere (2022) point out other sources can be tracked down to possible conflicting policy aims between the EU ETS and national policies (e.g., waterbed effect). Uncertainty on the policy mix is likely to increase according to different transition scenarios to a low-carbon economy (NGFS, 2019).

3. Data and methodology

3.1 Data

A diverse array of time series will be employed to perform this analysis encompassing the multiple dimensions involved. For a decade (2008-2019), monthly data will be considered for the analysis. Data on monthly EUA stock prices are taken from ICAP[3], SendeCO2[4] 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)[5] (so-called Reference Approach). The industrial dimension, the Global Index of Real Economic Activities[6] (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). 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[7]. For commodity prices, natural gas and oil come from the World Bank Commodity Price Data repository for the Netherlands Title Transfer Facility[8] (NTTF) and Brent, respectively. Electricity prices are those of the Nord Pool Power Market encompassing Northern and Baltic regions. To proxy coal price at EU level, data on the average price of the Rotterdam Coal Futures from ICE market will be considered. Climate and weather data are stored in the IEA

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

[4] https://www.sendeco2.com/it/prezzi-co2

[5] The dataset is available upon request, for deeper insights on the methodology see (Quatrosi, 2020)

[6] 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

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

[8] 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 excludes UK.

Weather Energy Tracker, held by IEA and Mediterranean Centre for Climate Change (CMCC). As the database contains country-level data, the series employed has been achieved by averaging the values of the 31 Countries under the ETS. Climate/Weather data comprise monthly averages of temperatures (i.e., min, max), rainfall (maximum rainfall), wind speed (10 mt). Table 1 summarizes the main statistics for the series.

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

As tests on stationarity will be commented later on (Table 3), the preliminary analysis proceeds with the correlation matrix of the series. As it is possible to appreciate (Table 2), there are quite a few high correlations between temperature and wind speed. CO2 shows a significant but negative correlation with the temperature set and positive with industrial production and commodities (e.g., natural gas price, oil, electricity) for the variables of interest. There is a relatively weak but positive correlation with EUA prices and a negative with the STOXX index. On the other hand, EUA prices positively correlate with the Kilian Index and Nord Pool electricity prices. Positive yet weak correlation for the financial dimension and the other commodities.

Table 3 Correlation matrix

	Kilian Index	Brent	CO2	EUA	Max Temperature	Tot Rainfall	Min Temperature	Wind Speed 10mt	Dutch TTF	North Pool Electricity	STOXX50e	Rotterdam Coal Futures
Kilian Index	1	0.357	0.242	0.660	0.054	0.019	0.070	-0.033	0.352	0.380	0.096	0.702
Brent	0.357	1	0.273	0.145	0.112	-0.029	0.075	-0.080	0.712	0.271	-0.232	0.626
CO_2	0.242	0.273	1	0.118	-0.717	0.131	-0.684	0.645	0.553	0.409	-0.132	0.352
EUA	0.660	0.145	0.118	1	0.006	-0.114	-0.008	0.031	0.240	0.554	0.161	0.613
Max Temperature	0.054	0.112	-0.717	0.006	1	-0.111	0.962	-0.872	-0.079	-0.289	-0.025	0.040
Tot Rainfall	0.019	-0.029	0.131	-0.114	-0.111	1	-0.014	0.200	0.071	-0.021	-0.123	-0.047
Min Temperature	0.070	0.075	-0.684	-0.008	0.962	-0.014	1	-0.828	-0.078	-0.331	-0.006	0.041
Wind Speed 10mt	-0.033	-0.080	0.645	0.031	-0.872	0.200	-0.828	1	0.094	0.153	0.103	-0.014
Dutch TTF	0.352	0.712	0.553	0.240	-0.079	0.071	-0.078	0.094	1	0.344	-0.399	0.554
North Pool Electricity	0.380	0.271	0.409	0.554	-0.289	-0.021	-0.331	0.153	0.344	1	-0.153	0.487
STOXX50E	0.096	-0.232	-0.132	0.161	-0.025	-0.123	-0.006	0.103	-0.399	-0.153	1	0.075
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

3.2 Methodology

To account for the multiple dimensions of the series subject of analysis, Hierarchical Vector Autoregressive Model (HVAR) will be employed addressing this high dimensional context. This methodology was first introduced in W. B. Nicholson et al. (2020) as a more suitable solution for forecasting exercises in high dimensional contexts with respect to 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). HVAR encodes lag order selection into a convex regularization that simultaneously addresses dimensionality and lag order selection. Unlike Bayesian models and lasso-based models, it provides interpretable insights on the contribution of each time series on the forecasting exercise. While aiming at interpretability, HVAR introduces maximization in lag order selection dealing with increasing maximal order. In fact, in other models, as lag order increases forecasting performances tend to degrade. Lasso-based VAR are conceived under the assumption the matrix of the coefficient in high dimensional context is sparse (Song and Bickel, 2011). Starting from the matrix representation of a $VAR(p)_k$ model for a set of k time series of length T[9]:

$$Y = v1^{\intercal} + \Phi Z + U \qquad [1]$$

Where Φ controls the dynamic dependent of the ith component of y_t on the jth component of y_{t-1}. Some contributions have highlighted how the estimation of the least square coefficient matrix might be challenging unless T is large. Furthermore, for large (even medium) k, the matrix of the coefficients is sparse even with regards to the true Data Generating Process (DGP) (Davis et al. 2012). Some authors, as 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 modelling, 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 component of the series 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 on Equation 1, being L a kxk matrix of elementwise coefficient lags

$$L_{ij} = max\{\ell{:}\phi_{ij}{}^{(\ell)} \neq 0\} \qquad [2]$$

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 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 and Discussion

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

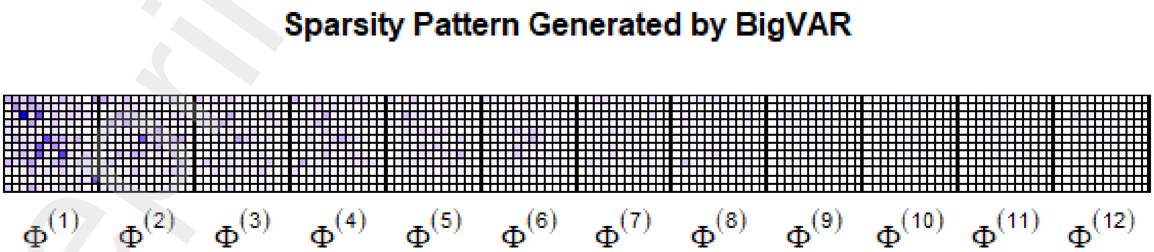
Table 1 Multiple Stationarity Tests

[9] For the notation see Appendix 1

	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

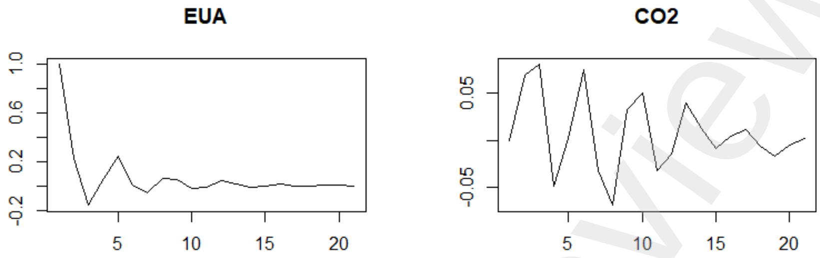
To tackle the different scales and units of measures of the variables, the series will be standardized to refine better the subsequent analyses as suggested by James et al. (2013). Since there is no consistent way for choosing the maximum lag order that applies to HVAR estimation, W. Nicholson et al. (2017) suggest the parameter p will be set according to the frequency of the time series considered (e.g., 12 for monthly series). Once estimated the coefficient, the cross-validation will be performed by dividing the dataset into three parts T/3; 2T/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 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 terms, the coefficients of the lagged variables tend to influence more the estimation than the single marginal equations.

Figure 1 Sparsity Matrix of Elementwise HVAR



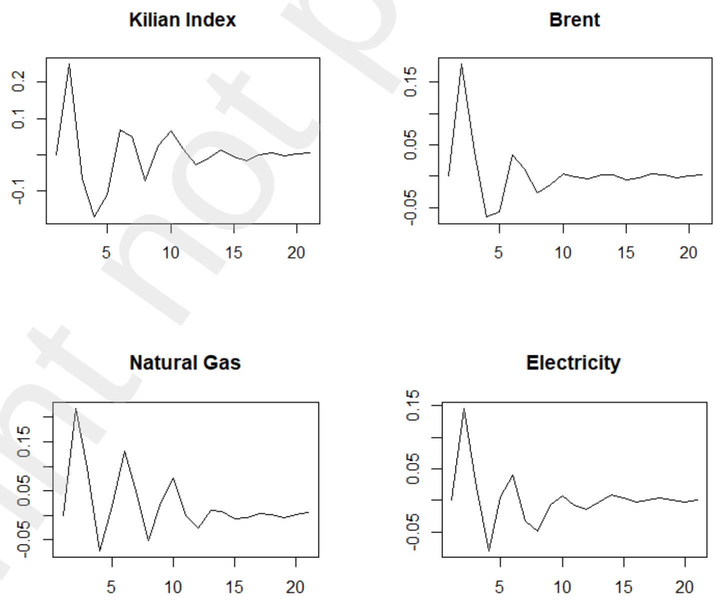
As for the optimization procedure, the chart in Appendix 2 shows a parabolic shape for the penalization term λ. To show the primary hypothesis, namely, the response of a shock of the carbon price to emission trends from the energy sector, the Impulse-Response Function (IRF) has been modeled out of the last estimation of the HVAR. The computation of the IRF follows Pesaran and Shin (1998) to relax some further limitations, not taking into account the order of the variables. Figures 2-3 show the response of carbon dioxide emission trends and relevant system variables to a shock on EUA prices. Figures 2-3 show the specification of the model considering temperatures (min, max), wind speed at 10 mt, total rainfall. Focusing on the response of carbon dioxide emissions, it is possible to appreciate how the shock generates a wild trend for future emissions, with intensity progressively fading away as time goes by.

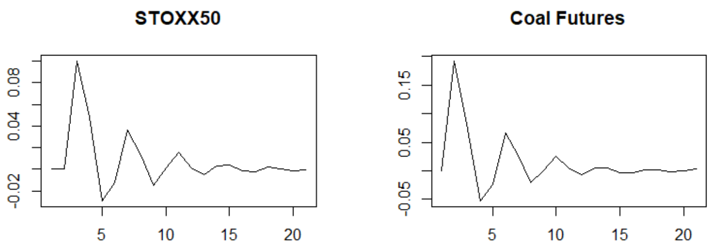
Figure 2 Impulse-Response Function CO_2 emissions



As for other relevant variables of the system considered, Figure 3 models IRF for commodity prices, production, and financial indexes, EUA appears to exert a downward trend for Kilian Index and specific commodity prices (e.g., Brent, Natural Gas) that becomes clearer (yet less intensive) over time. As for the STOXX50 index and Nord Pool electricity, a carbon price shock appears to exert a quite intense response, at least in the nearer future.

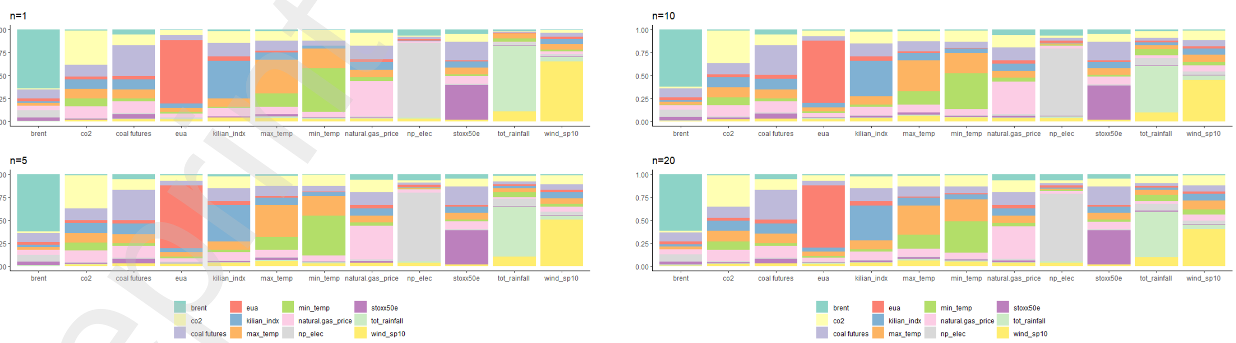
Figure 3 Impulse-Response Relevant covariates





Decomposition (FEVD) is depicted in Figure 7, respectively, to 1, 5, 10, and 20 steps ahead. In line with the previous analysis, the computation of FEVD follows the approach as in Pesaran and Shin (1998). The Figure shows how much of the variance in error forecasting of every variable can be explained by the other variables. The higher is the contribution of other variables, the more integrated the system is, and the more robust are results and trends of the IRF Lütkepohl (2005). As shown in Figure 4, the variables themselves exert a higher contribution to the variance. For the variable of interest (e.g., CO_2), other influences mostly come from the climate/weather set of variables and commodity prices. Kilian Index and Natural Gas and Coal price explain the carbon dioxide variance between 10%-15% of the carbon dioxide variance. In this sense, according to other findings in the literature, (Khalili et al. 2012; Du et al. 2018), the influence of commodity prices could be considered to a greater extent as prices influence commodity demand and supply. Other factors influencing carbon emissions (e.g., industrial production) appear to be in line with Declercq et al. (2011), Dong et al. (2019), Zeng et al. (2021). As for the influence of EUA price, despite relatively low (6%-7%), the value slightly increases over time. All the variables show external influence in their variance composition regarding the broader system. However, the contribution of those variables appears still to be limited. The most significant influence of EUA price ranges between 4%-5% for (max) temperature, natural gas price, Kilian Index. On the other hand, a carbon price is more influenced by commodity prices and temperatures (min, max) than the financial index, rainfall, and wind speed. This latter finding sheds further light on the analysis of the relationship of wind characteristics (e.g., speed, direction) as one other determinant of carbon prices (Chevallier, 2012a). A more country-specific analysis is deemed appropriate to disentangle more consistent results despite the evident yet negligible influence. As for the other variables influencing EU ETS prices, these findings are in line with Mansanet-Bataller et al. (2007), Alberola et al. (2008); Aatola et al. (2013). As for the behaviour over time, Figure 4 does not show any marked difference among the variables.

Figure 4 Forecast Error Variance Decomposition (Specification I)



5. Conclusions

While improvements in the so-called *carbon price gap* signal a better use of market-based instruments reducing CO_2 emissions, there are concerns 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 (about 1.5% of 2018 the EU GDP) to comply with the EU Green Deal objectives by 2030. In this sense, the EU budget will play a pivotal role in fostering a societal sustainability transition. For this purpose, the EU is planning to earmark

20% of the revenue stream coming from the EU ETS. As from the last account the revenue flow of the EU mechanism amounted to €14 billion in 2019 (€5.7 billion in the half of 2020), with €57 billion of revenues generated within 2012 and June 2020 (Nissen et al., 2020). Furthermore, a sustained price of allowance permits ensured a consistent revenue flow despite the lower level of transactions, especially about the most recent events (Azarova and Mier, 2021; Borghesi and Flori, 2019; Nissen et al., 2020; Quemin 2022). If the short and medium-term effects of COVID-19 pandemics on carbon prices might be predictable, still uncertain are the long-term effects coupled with the outcome of Brexit. By all means, Verde et al. (2021) demonstrate factors such as policy interplay (e.g., waterbed effect) appear to be key issues undermining price stability, hindering concrete abatement efforts, and in turn, a more coordinated framework tackling climate and environmental issues. This work tries to provide ulterior insights on the effect of the emission trading scheme at the EU level, considering the broader system (environmental, climate, economic, financial) adopting a more suitable methodology. Hierarchical VAR has been conceived for high dimensional contexts providing interpretable results taking into account the single characteristics of the series considered. As already pointed out, 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. Main factors influencing EUA price level have been identified in an oversupply of permits during the first phases, issues related to the implementation of national policies in ETS-sectors, and a perceived lack of political commitment. Over the years, the progressive set of reforms (Phase I, II, III, IV) has tried to build a more reliable mechanism introducing price adjustments tools and the very auctioning of permits. The literature has also focused on the determinants of carbon prices and studies on the effectiveness of the policy. Those latter have been mainly conducted on a national basis confronting ETS with national policies. This work employs time series econometrics coupled with lasso-based regularization to provide new insights on the effectiveness and integration of the EU ETS considering economy, finance, energy, climate, environment. HVAR appears to better address simultaneously reduction of dimensionality and lag order selection. This provided interpretable results that have been used to model IR functions and FEVD analysis. The IR functions highlighted how a shock on carbon price will generate mostly a negative response to the set of variables considered. On the other hand, from FEVD it was possible to assess that effective influence of carbon prices on those variables was still weak. There appear to be other factors that exert a stronger influence on carbon dioxide with respect to EUA prices (e.g., climatic/meteorological, industrial performances, natural gas). Furthermore, results align with the preliminary analyses (e.g., correlation matrix) and the literature pointing out an influence of carbon prices on industrial performances, commodities, (extreme) temperatures. The lack of influence on financial markets could be explained by the fact that not all the sectors are included in the EU ETS. Overall, the magnitude of influence of carbon price towards the other variables is relatively weak for all the periods considered. On the other hand, the IRF plot has shown a negative pattern of the response of those variables to a shock on EUA prices. Results with other model specifications confirmed if not highlighted the findings also in line with the literature. In this sense, the choice of a more flexible methodology (HVAR) and the computation of IRF following the approach in Pesaran and Shin (1998) provided a more flexible environment to account for the diverse dimension of the system subject of analysis as suggested by Chevallier (2011b). These findings provide ulterior insights to policymakers for better taking into account 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. Results show the still relative prospective influence of carbon prices towards relevant variables considering the broader system. These findings should also be contextualized in light of the recent reforms of the EU ETS (Phase IV) that are not considered in this work. Factors influencing the effectiveness of the policy can be tracked down to the existence of (conflicting) environmental policies at national levels along with uncertainty over a sound price adjustment mechanism (Market Stability Reserve, price floor) that are still object of discussion for policymakers. A more active dialogue between national and EU policymakers should lead to a comprehensive policy mix avoiding overlapping aims. 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 channel funds towards sustainable investments. Even though EUA has been included as a financial instrument by the recent EU financial directive (MiFID2), apparently, carbon allowances are not enough considered by financial players. In this perspective, the huge process of reform affecting the financial sector (e.g., Taxonomy) should be designed considering the comprehensive array of policies from multiple aspects. Among the consistent literature on EU ETS and emission trading, this work tries to shed light on how this climate policy's current and potential integration with the broader system. This will be at the basis to promote a complete transition to sustainability in light of the problem's complexity and multi-faceted nature.

Appendix 1

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

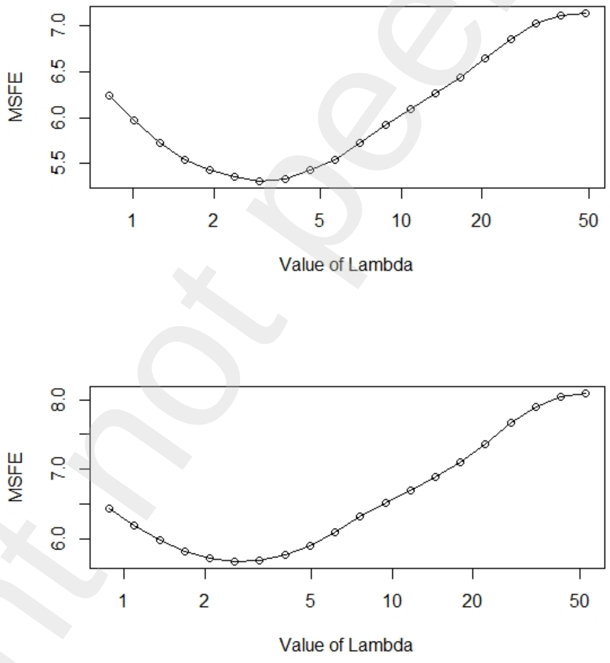
$$Y = [y_1 \ldots y_T]\ (k\ x\ T);\ \ Z = [z_1 \ldots z_T](kp\ x\ 1);$$

$$z = [y^{\intercal}{}_{t-1} \ldots y^{\intercal}{}_{t-p}](kp\ x\ T);\ U = [u_1 \ldots u_T]\ (k\ x\ T);$$

$$1 = [1 \ldots 1]^{\intercal}\ (T\ x\ 1);\ \ \Phi = [\Phi^{(1)} \ldots \Phi^{(p)}]\ (k\ x\ kp)$$

Appendix 2

Figure 5 Lamba Plot I-II Specification



References

Aatola, Piia, Markku Ollikainen, and Anne Toppinen. 2013. 'Price Determination in the EU ETS Market: Theory and Econometric Analysis with Market Fundamentals'. Energy Economics 36 (March): 380–95. https://doi.org/10.1016/j.eneco.2012.09.009.

Abrell, J., Kosch, M., & Rausch, S. (2022). How effective is carbon pricing?—A machine learning approach to policy evaluation. Journal of Environmental Economics and Management, 112, 102589. https://doi.org/10.1016/j.jeem.2021.102589

Alberola, Emilie, Julien Chevallier, and Benoı̂t Chèze. 2008. 'Price Drivers and Structural Breaks in European Carbon Prices 2005–2007'. Energy Policy 36 (2): 787–97. https://doi.org/10.1016/j.enpol.2007.10.029.

Anderson, Barry, and Corrado Di Maria. 2011. 'Abatement and Allocation in the Pilot Phase of the EU ETS'. Environmental and Resource Economics 48 (1): 83–103. https://doi.org/10.1007/s10640-010-9399-9.

Andor, Mark A., Manuel Frondel, and Stephan Sommer. 2016. 'Reforming the EU Emissions Trading System: An Alternative to the Market Stability Reserve'. Intereconomics 51 (2): 87–93. https://doi.org/10.1007/s10272-016-0582-2.

Asian Development Bank. 2015. Emission Trading Schemes and Their Linkng: Challenges and Opportunities in Asia and the Pacific. Asian Development Bank. https://www.adb.org/sites/default/files/publication/182501/emissions-trading-schemes.pdf.

Athey, S. (2017). Beyond prediction: Using big data for policy problems. Science, 355(6324), 483–485. https://doi.org/10.1126/science.aal4321

Athey, S., & Imbens, G. W. (2017). The State of Applied Econometrics: Causality and Policy Evaluation. Journal of Economic Perspectives, 31(2), 3–32. https://doi.org/10.1257/jep.31.2.3

Azarova, V., and M. Mier. 2021. 'Market Stability Reserve under Exogenous Shock: The Case of COVID-19 Pandemic'. Applied Energy 283. https://doi.org/10.1016/j.apenergy.2020.116351.

Bagheri, Ehsan, and Seyed Babak Ebrahimi. 2020. 'Estimating Network Connectedness of Financial Markets and Commodities'. Journal of Systems Science and Systems Engineering 29 (5): 572–89. https://doi.org/10.1007/s11518-020-5465-1.

Blyth, William, and Derek Bunn. 2011. 'Coevolution of Policy, Market and Technical Price Risks in the EU ETS'. Energy Policy, At the Crossroads: Pathways of Renewable and Nuclear Energy Policy in North Africa, 39 (8): 4578–93. https://doi.org/10.1016/j.enpol.2011.04.061.

Borghesi, Simone, and Andrea Flori. 2019. 'With or without U(K): A Pre-Brexit Network Analysis of the EU ETS'. Edited by Alessandro Spelta. PLOS ONE 14 (9): e0221587. https://doi.org/10.1371/journal.pone.0221587.

Borghesi, Simone, Massimiliano Montini, and Alessandra Barreca. 2016. The European Emission Trading System and Its Followers: Comparative Analysis and Linking Perspectives. SpringerBriefs in Environmental Science. Springer International Publishing. https://doi.org/10.1007/978-3-319-31186-9.

Brink, Corjan, and Herman R.J. Vollebergh. 2020. 'What Can We Learn from EU ETS?' Ifo DICE Report 18 (01): 8.

Brouwers, Roel, Frederiek Schoubben, Cynthia Van Hulle, and Steve Van Uytbergen. 2016. 'The Initial Impact of EU ETS Verification Events on Stock Prices'. Energy Policy 94 (July): 138–49. https://doi.org/10.1016/j.enpol.2016.04.006.

Bruninx, K., & Ovaere, M. (2022). COVID-19, Green Deal and recovery plan permanently change emissions and prices in EU ETS Phase IV. Nature Communications, 13(1), 1165. https://doi.org/10.1038/s41467-022-28398-2

Bruninx, K., & Ovaere, M. (2022). COVID-19, Green Deal and recovery plan permanently change emissions and prices in EU ETS Phase IV. Nature Communications, 13(1), 1165. https://doi.org/10.1038/s41467-022-28398-2

Burke, M., M. Craxton, C. D. Kolstad, C. Onda, H. Allcott, E. Baker, L. Barrage, et al. 2016. 'Opportunities for Advances in Climate Change Economics'. Science 352 (6283): 292–93. https://doi.org/10.1126/science.aad9634.

Chevallier, Julien. 2011a. 'Carbon Price Drivers: An Updated Literature Review', 9.

———. 2011b. 'The Impact of Nonlinearities for Carbon Markets Analyses'. International Economics 126–127 (February): 131–50. https://doi.org/10.1016/S2110-7017(13)60040-2.

Convery, F. J. 2008. 'Reflections--The Emerging Literature on Emissions Trading in Europe'. Review of Environmental Economics and Policy 3 (1): 121–37. https://doi.org/10.1093/reep/ren020.

Creti, Anna, Pierre-André Jouvet, and Valérie Mignon. 2012. 'Carbon Price Drivers: Phase I versus Phase II Equilibrium?' Energy Economics 34 (1): 327–34. https://doi.org/10.1016/j.eneco.2011.11.001.

Davis, Richard A., Pengfei Zang, and Tian Zheng. 2012. 'Sparse Vector Autoregressive Modeling'. ArXiv:1207.0520 [Stat], July. http://arxiv.org/abs/1207.0520.

Dechezleprêtre, Antoine, Daniel Nachtigall, and Frank Venmans. 2018. 'THE JOINT IMPACT OF THE EUROPEAN UNION EMISSIONS TRADING SYSTEM ON CARBON EMISSIONS AND ECONOMIC PERFORMANCE'. ECONOMICS DEPARTMENT WORKING PAPERS, no. 1515: 57.

Declercq, Bruno, Erik Delarue, and William D'haeseleer. 2011. 'Impact of the Economic Recession on the European Power Sector's CO2 Emissions'. Energy Policy 39 (3): 1677–86. https://doi.org/10.1016/j.enpol.2010.12.043.

Delarue, Erik D., A. Denny Ellerman, and William D. D'Haeseleer. 2010. 'SHORT-TERM CO2 ABATEMENT IN THE EUROPEAN POWER SECTOR: 2005–2006'. Climate Change Economics 01 (02): 113–33. https://doi.org/10.1142/S2010007810000108.

Dong, K., X. Dong, and C. Dong. 2019. 'Determinants of the Global and Regional CO2 Emissions: What Causes What and Where?' Applied Economics 51 (46): 5031–44. https://doi.org/10.1080/00036846.2019.1606410.

Du, Gang, Chuanwang Sun, Xiaoling Ouyang, and Chi Zhang. 2018. 'A Decomposition Analysis of Energy-Related CO2 Emissions in Chinese Six High-Energy Intensive Industries'. Journal of Cleaner Production 184 (May): 1102–12. https://doi.org/10.1016/j.jclepro.2018.02.304.

Ellerman, A. Denny, and Barbara K. Buchner. 2008. 'Over-Allocation or Abatement? A Preliminary Analysis of the EU ETS Based on the 2005–06 Emissions Data'. Environmental and Resource Economics 41 (2): 267–87. https://doi.org/10.1007/s10640-008-9191-2.

Ellerman, A. Denny, and Stephan Feilhauer. 2008. 'A Top-down and Bottom-up Look at Emissions Abatementin Germany in Response to the EU ETS'. Center for Energy and Environmental Policy Research, Working Paper Series, 08 (17): 22.

Eugenia Sanin, María, Francesco Violante, and María Mansanet-Bataller. 2015. 'Understanding Volatility Dynamics in the EU-ETS Market'. Energy Policy 82 (July): 321–31. https://doi.org/10.1016/j.enpol.2015.02.024.

European Parliament. 2003. Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 Establishing a Scheme for Greenhouse Gas Emission Allowance Trading within the Community and Amending Council Directive 96/61/EC (Text with EEA Relevance). 275. Vol. OJ L. http://data.europa.eu/eli/dir/2003/87/oj/eng.

———. 2014. 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. 173. Vol. OJ L. http://data.europa.eu/eli/dir/2014/65/oj/fra.

Grosjean, G., W. Acworth, C. Flachsland, and R. Marschinski. 2016. 'After Monetary Policy, Climate Policy: Is Delegation the Key to EU ETS Reform?' Climate Policy 16 (1): 1–25. https://doi.org/10.1080/14693062.2014.965657.

Gugler, K., Haxhimusa, A., & Liebensteiner, M. (2021). Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables. Journal of Environmental Economics and Management, 106, 102405. https://doi.org/10.1016/j.jeem.2020.102405

High-level Commission on Carbon Prices. 2017. Report of the High-Level Commission on Carbon Prices. World Bank Group. carbonpricingleadership.org.

Hitzemann, Steffen, Marliese Uhrig-Homburg, and Karl-Martin Ehrhart. 2015. 'Emission Permits and the Announcement of Realized Emissions: Price Impact, Trading Volume, and Volatilities'. Energy Economics 51 (September): 560–69. https://doi.org/10.1016/j.eneco.2015.07.007.

Hourcade, Jean-Charles, and Priyadarshi Shukla. 2013. 'Triggering the Low-Carbon Transition in the Aftermath of the Global Financial Crisis'. Climate Policy 13 (sup01): 22–35. https://doi.org/10.1080/14693062.2012.751687.

Intergovernmental Panel on Climate Change. 2014. Climate Change 2014 Mitigation of Climate Change: Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781107415416.

James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani, eds. 2013. An Introduction to Statistical Learning: With Applications in R. Springer Texts in Statistics 103. New York: Springer.

Ji, Chang-Jing, Xiao-Yi Li, Yu-Jie Hu, Xiang-Yu Wang, and Bao-Jun Tang. 2019. 'Research on Carbon Price in Emissions Trading Scheme: A Bibliometric Analysis'. Natural Hazards 99 (3): 1381–96. https://doi.org/10.1007/s11069-018-3433-6.

Ji, Qiang, Tongshui Xia, Fan Liu, and Jin-Hua Xu. 2019. 'The Information Spillover between Carbon Price and Power Sector Returns: Evidence from the Major European Electricity Companies'. Journal of Cleaner Production 208 (January): 1178–87. https://doi.org/10.1016/j.jclepro.2018.10.167.

Jiménez-Rodríguez, Rebeca. 2019. 'What Happens to the Relationship between EU Allowances Prices and Stock Market Indices in Europe?' Energy Economics 81 (June): 13–24. https://doi.org/10.1016/j.eneco.2019.03.002.

Känzig, D. R. (2021). The Unequal Economic Consequences of Carbon Pricing. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3786030

Khalili Araghi, M., Gh.A. Sharzei, and S. Barkhordari. 2012. 'A Decomposition Analysis of CO2 Emissions Related to Energy Consumption in Iran'. Journal of Environmental Studies 38 (61): 93–104.

Kilian, Lutz, and Xiaoqing Zhou. 2018. 'Modeling Fluctuations in the Global Demand for Commodities'. Journal of International Money and Finance 88 (November): 54–78. https://doi.org/10.1016/j.jimonfin.2018.07.001.

Kilian, Lutz. 2009. 'Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market'. American Economic Review 99 (3): 1053–69. https://doi.org/10.1257/aer.99.3.1053.

———. 2019. 'Measuring Global Real Economic Activity: Do Recent Critiques Hold up to Scrutiny?' Economics Letters 178 (May): 106–10. https://doi.org/10.1016/j.econlet.2019.03.001.

Koch, Nicolas, and Houdou Basse Mama. 2019. 'Does the EU Emissions Trading System Induce Investment Leakage? Evidence from German Multinational Firms'. Energy Economics 81 (June): 479–92. https://doi.org/10.1016/j.eneco.2019.04.018.

Koch, Nicolas, Sabine Fuss, Godefroy Grosjean, and Ottmar Edenhofer. 2014. 'Causes of the EU ETS Price Drop: Recession, CDM, Renewable Policies or a Bit of Everything?—New Evidence'. Energy Policy 73 (October): 676–85. https://doi.org/10.1016/j.enpol.2014.06.024.

Laing, Timothy, Misato Sato, Michael Grubb, and Claudia Comberti. 2014. 'The Effects and Side-Effects of the EU Emissions Trading Scheme'. WIREs Climate Change 5 (4): 509–19. https://doi.org/10.1002/wcc.283.

Lecuyer, Oskar, and Philippe Quirion. 2013. 'Can Uncertainty Justify Overlapping Policy Instruments to Mitigate Emissions?' Ecological Economics 93 (September): 177–91. https://doi.org/10.1016/j.ecolecon.2013.05.009.

Löschel, Andreas, Benjamin Johannes Lutz, and Shunsuke Managi. 2019. 'The Impacts of the EU ETS on Efficiency and Economic Performance – An Empirical Analyses for German Manufacturing Firms'. Resource and Energy Economics 56 (May): 71–95. https://doi.org/10.1016/j.reseneeco.2018.03.001.

Lütkepohl, Helmut. 2005. New Introduction to Multiple Time Series Analysis. Berlin: New York : Springer.

Mansanet-Bataller, Maria, Angel Pardo, and Enric Valor. 2007. 'CO_2 Prices, Energy and Weather'. The Energy Journal 28 (3): 21.

Marin, Giovanni, Marianna Marino, and Claudia Pellegrin. 2018. 'The Impact of the European Emission Trading Scheme on Multiple Measures of Economic Performance'. Environmental and Resource Economics 71 (2): 551–82. https://doi.org/10.1007/s10640-017-0173-0.

Martin, Ralf, Mirabelle Muûls, and Ulrich J Wagner. 2016. 'The Impact of the EU ETS on Regulated Firms: What Is the Evidence after 10 Years?', 33.

McGuinness, Meghan, and A Denny Ellerman. 2008. 'CO2 Abatement in the UK Power Sector: Evidence from the EU ETS Trial Period', 18.

Naegele, Helene, and Aleksandar Zaklan. 2019. 'Does the EU ETS Cause Carbon Leakage in European Manufacturing?' Journal of Environmental Economics and Management 93 (January): 125–47. https://doi.org/10.1016/j.jeem.2018.11.004.

Network for Greening the Financial System. 2019. 'A Call for Action- Climate Change as a Source of Financial Crisis'. https://www.ngfs.net/en.

Nicholson, William B., Ines Wilms, Jacob Bien, and David S. Matteson. 2020. 'High Dimensional Forecasting via Interpretable Vector Autoregression'. ArXiv:1412.5250 [Stat], September. http://arxiv.org/abs/1412.5250.

Nicholson, William, David Matteson, and Jacob Bien. 2017. 'BigVAR: Tools for Modeling Sparse High-Dimensional Multivariate Time Series'. ArXiv:1702.07094 [Stat], February. http://arxiv.org/abs/1702.07094.

Nissen, Christian, Johanna Cludius, Verena Graichen, and Jakob Graichen. 2020. 'The EU Emissions Trading System in Numbers', 57.

Oberndorfer, Ulrich. 2009. 'EU Emission Allowances and the Stock Market: Evidence from the Electricity Industry'. Ecological Economics, Participation and Evaluation for Sustainable River Basin Governance, 68 (4): 1116–26. https://doi.org/10.1016/j.ecolecon.2008.07.026.

OECD. 2016. Effective Carbon Rates: Pricing CO2 through Taxes and Emissions Trading Systems. OECD. https://doi.org/10.1787/9789264260115-en.

———. 2018. Effective Carbon Rates 2018: Pricing Carbon Emissions Through Taxes and Emissions Trading. OECD. https://doi.org/10.1787/9789264305304-en.

Pearce, D. 2003. 'The Social Cost of Carbon and Its Policy Implications'. Oxford Review of Economic Policy 19 (3): 362–84. https://doi.org/10.1093/oxrep/19.3.362.

Perino, Grischa, and Maximilian Willner. 2016. 'Procrastinating Reform: The Impact of the Market Stability Reserve on the EU ETS'. Journal of Environmental Economics and Management, The economics of the European Union Emission Trading System (EU ETS) market stability reserve, 80 (November): 37–52. https://doi.org/10.1016/j.jeem.2016.09.006.

Perino, Grischa, Robert Ritz, and Arthur van Benthem. 2019. 'Understanding Overlapping Policies: Internal Carbon Leakage and the Punctured Waterbed'. w25643. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w25643.

Pesaran, H. Hashem, and Yongcheol Shin. 1998. 'Generalized Impulse Response Analysis in Linear Multivariate Models'. Economics Letters 58 (1): 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0.

Quemin, S. (2022). Raising climate ambition in emissions trading systems: The case of the EU ETS and the 2021 review. Resource and Energy Economics, 68, 101300. https://doi.org/10.1016/j.reseneeco.2022.101300

Schusser, Sandra, and Jūratė Jaraitė. 2018. 'Explaining the Interplay of Three Markets: Green Certificates, Carbon Emissions and Electricity'. Energy Economics 71 (March): 1–13. https://doi.org/10.1016/j.eneco.2018.01.012.

Shahnazari, Mahdi, Adam McHugh, Bryan Maybee, and Jonathan Whale. 2017. 'Overlapping Carbon Pricing and Renewable Support Schemes under Political Uncertainty: Global Lessons from an Australian Case Study'. Applied Energy 200 (August): 237–48. https://doi.org/10.1016/j.apenergy.2017.05.038.

Soliman, Alaa M., and Muhammad Ali Nasir. 2019. 'Association between the Energy and Emission Prices: An Analysis of EU Emission Trading System'. Resources Policy 61 (June): 369–74. https://doi.org/10.1016/j.resourpol.2018.12.005.

Song, Song, and Peter J. Bickel. 2011. 'Large Vector Auto Regressions'. ArXiv:1106.3915 [q-Fin, Stat], June. http://arxiv.org/abs/1106.3915.

Teixidó, Jordi, Stefano F. Verde, and Francesco Nicolli. 2019. 'The Impact of the EU Emissions Trading System on Low-Carbon Technological Change: The Empirical Evidence'. Ecological Economics 164 (October): 106347. https://doi.org/10.1016/j.ecolecon.2019.06.002.

Tvinnereim, Endre, and Michael Mehling. 2018. 'Carbon Pricing and Deep Decarbonisation'. Energy Policy 121 (October): 185–89. https://doi.org/10.1016/j.enpol.2018.06.020.

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. Journal of Economic Perspectives, 28(2), 3–28. https://doi.org/10.1257/jep.28.2.3

Verde, Stefano F., Giulio Galdi, Isabella Alloisio, and Simone Borghesi. 2021. 'The EU ETS and Its Companion Policies: Any Insight for China's ETS?' Environment and Development Economics, March, 1–19. https://doi.org/10.1017/S1355770X20000595.

World Bank. 2020. 'State and Trends of Carbon Pricing 2020'. Washington, DC: World Bank and International Carbon Action Partnership.

https://openknowledge.worldbank.org/bitstream/handle/10986/33809/9781464815867.pdf?sequence=4&isAllowed=y.

Zeng, Chen, Lindsay C. Stringer, and Tianyu Lv. 2021. 'The Spatial Spillover Effect of Fossil Fuel Energy Trade on CO2 Emissions'. Energy 223 (May): 120038. https://doi.org/10.1016/j.energy.2021.120038.

Zhu, Huiming, Yiding Tang, Cheng Peng, and Keming Yu. 2018. 'The Heterogeneous Response of the Stock Market to Emission Allowance Price: Evidence from Quantile Regression'. Carbon Management 9 (3): 277–89. https://doi.org/10.1080/17583004.2018.1475802.