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The determinants of CO_2 prices in the EU emission trading system

Yuliya Lovcha [a,*], Alejandro Perez-Laborda [a], Iryna Sikora [b]

[a] Universitat Rovira-i-Virgili, and ECO-SOS, Spain
[b] Principal Economist. Environmental Policy. Ricardo Energy & Environment, Spain

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ABSTRACT

In 2005, the European Union launched its Emissions Trading System (ETS), the first and one of the largest international carbon markets aimed at reducing member states' CO2 emissions. Policymakers tend to use the carbon price as an indicator of the "health" and effectiveness of the ETS mechanism, although this measure is influenced by many other energy and climate policies, energy market fundamentals, and speculative shocks. This paper develops a model that links the energy sector (oil, natural gas, coal, electricity prices, and the share of fossil fuels in electricity generation), economic activity, and the carbon price. The model can be used as a monitoring tool for carbon price dynamics. We represent the model empirically through a Structural Vector Autoregression and use frequency-domain analysis to distinguish the effects of changes in fundamental factors from shocks to market microstructure. Our empirical results show that up to 90% (65% on average) of the fluctuations in the carbon price, adjusted for supply effects, are explained by fluctuations in fundamental market variables; however, the individual contributions are not stable. Overall, our results suggest that the ETS has started to work well.

1. Introduction

European Union created the Emission Trading System (ETS) 15 years ago as part of its climate action plan. It consists of limiting the number of issued CO_2 allowances and selling them via auction to eligible emitting entities, which can trade them further on a secondary market. In this way, a market for CO_2 is established. If the CO_2 emission permits price (carbon price, henceforth) becomes high enough, some industrial installations may find it cheaper to implement energy efficiency initiatives or switch to alternative fuels associated with lower emissions than to continue paying for allowances.

Since its inception in 2005, the ETS system has gone through four implementation phases, with Phase 4 covering the period 2021–2030. In all phases, the ETS system is based on market forces: the EU sets and limits supply, and the market determines demand. The carbon price is therefore determined by the interaction of these two market forces. Once the amount of CO2 available to the market is set, the demand side alone decides the price. In this case, demand may not provide prices high enough to switch to alternative fuels and implement other emission reduction measures. Such situations endanger technological change and the achievement of climate protection targets, as happened in 2010 due to the global financial crisis.

In this paper we study the determinants of carbon price dynamics. We develop a theoretical framework to build an empirical model linking the energy sector, economic activity, and the carbon price. Many other papers have studied the determinants of the carbon price. For example, Hintermann et al. [1] provide an excellent review of the ETS modeling literature for Phases I and II. Recent studies include Ji et al. [2], Chevalier et al. [3], Jimenez-Rodriguez [4], Wang and Guo [5], Tan et al. [6], Gong et al. [7], Tan and Wang [8].

Our work makes three important contributions to this literature. We first develop a comprehensive theoretical model for carbon price determination. The model incorporates the share of fossil fuels in electricity generation among the carbon price determinants. This variable

* Corresponding autor at: Universitat Rovira-i-Virgili, Department of Economics, Av. Universitat 1, 43201 Reus, Spain.
E-mail address: yuliya.lovcha@urv.cat (Y. Lovcha).

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allows us to account for changes in fossil fuel demand due to renewable energy policies that are not adequately captured by other model variables such as energy prices or economic activity. Second, we propose an identification scheme to distinguish the effects of omitted policy and fundamental factors from carbon market speculation. The identification strategy, built in the frequency domain, assumes that long-term fluctuations in the carbon price due to the carbon market shock are entirely due to omitted policy and fundamental factors. At the same time, short-term fluctuations are (largely) due to speculation and market microstructure noise. Third, we empirically represent the model as a structural vector autoregressive (SVAR) model that we estimate dynamically over a rolling window. The SVAR allows us to quantify the impact of each variable on the carbon price and assess the evolution of this impact over time. To quantify the impacts, we rely on impulse response analysis (IRF) and spillover indices based on the connectedness framework of Diebold and Yilmaz [9,10]. The spillover indices are calculated using the frequency domain approach of Barunik and Krehlik [11] to distinguish between short-, medium- and long-term interactions.

The proposed model can be used for historical analysis of past policies, showing the relative importance of different factors in carbon price dynamics in each period and providing insights into why a particular policy worked or did not work. It can also be used for forward-looking analysis by providing answers to the likely magnitude of changes in carbon prices due to shocks in fundamental market variables, such as fossil fuel prices. In general, our model provides a valuable monitoring tool for carbon price dynamics. This knowledge can help EU policymakers anticipate market failure (rather than correcting it after the fact) and provide a timely signal to adjust the number of permits or other relevant policies. At the international level, the results provide useful information for policymakers designing and analyzing emissions trading schemes in other countries by showing the vulnerability of the European ETS to external factors.

As the carbon market is now largely financialized, the model can help investors optimize their portfolios and hedge risks. According to the results of Crossland et al. [12], the EU ETS is not information efficient, so in addition to constructing the optimal investment portfolio, information about the relationships between markets can be used to determine excess returns.

The paper is organized as follows. Section 2 summarizes the previous literature, highlighting the main differences with our work. Section 3 presents a theoretical model in which the carbon price interacts with other fundamental variables of the energy system. The econometric framework is presented in Section 4. Section 5 develops the empirical model and discusses the econometric strategy. Section 6 discusses the results. Finally, Section 7 presents the implications of our results and makes some concluding remarks.

2. Literature review

The EU ETS has attracted much attention from the scientific community. Most studies examine the main drivers of the carbon price, or the dynamic relationship between the carbon price and other energy markets. These two questions are closely related, as the financial integration across markets makes it difficult to determine whether a market is a driver or a follower.

Early research included pure, time-series modeling studies of carbon price (e.g., Paolella and Taschini [13]; Benz and Trück [14]; Daskalakis et al. [15]). However, most of the literature focuses on the determinants of carbon price. For example, Christiansen et al. [16] suggested that market fundamentals such as weather, fuel prices, fuel switching, and regulation play a significant role in determining the carbon price. Subsequent studies concluded that fuel price is one of the most important determinants of carbon price (e.g., Mansanet-Bataller et al. [17]; Alberola et al. [18]; Keppler and Mansanet-Bataller [19]; Hintermann [20]; Chevallier [21]; Creti et al. [22]; Aatola et al. [23]). Most of these authors also emphasized that economic activity is an important driver of carbon prices, generally using stock market indices as indicators of economic activity.

Even at this early stage, some authors emphasized that the relationship between carbon prices and other variables changes over time. For example, Alberola et al. [18] tested for structural breaks, Chevallier [21] used Markov switching VAR to account for possible nonlinearities, Creti et al. [22] analyzed the stability of the determinants of the carbon price during Phases I and II, Chevallier [24] evaluated the dynamic relationship between oil, gas, and carbon prices in BEKK, CCC, and DCC-MGARCH models. Hammoudeh et al. [25] used quantile regressions to determine the impact of energy prices on carbon price. In addition, Hammoudeh et al. [26] used impulse response analysis from a Bayesian SVAR model to analyze the dynamics of carbon pricing in response to changes in other energy prices. The authors found a positive impact from the oil price shock in the short run, negative impacts from the natural gas and electricity price shocks, and a statistically insignificant response from the coal price shock.

Chevallier et al. [3] applied a conditional Vine Copula approach to model the dependence structure between EU emission allowance returns and primary energy price returns (coal, gas, oil, and electricity). The authors found that the carbon price is only weakly related to energy prices, and that the link to oil and gas prices is negative. Also, Jimenez-Rodriguez [4] tested the causality between a common factor calculated from the main European stock market indices and EU ETS prices, concluding that there is a relationship between the stock market and the EU ETS.

Wang and Guo [5] and Ji et al. [2] estimated a moving window VAR on returns and volatilities of carbon and energy prices, and other variables, to quantify dynamic connectedness based on Diebold and Yilmaz [9,10]. Both papers highlighted the crucial role of Brent oil returns on carbon price returns. Ji et al. [2] found evidence of spillover effects from the carbon market to other energy markets and emphasize that electricity returns are the most important recipient of spillover effects in the system. Wang and Guo [5] also reported a significant spillover effect from natural gas to the carbon market. Tan and Wang [8] analyzed the quantile-based dependence between EU allowances, energy prices and macroeconomic risk factors. They found that the two variables have a significant impact on carbon pricing, although the magnitudes change during the three phases of the EU ETS.

In recent papers, Tan et al. [6] used the Modified Lanne-Nyberg DY variance decomposition to compute the directional connectedness in the "Carbon-Energy-Finance" system. They concluded that the carbon market is closely related to the stock and non-energy commodity markets and less related to the bond market. Zhao et al. [27] and Adekoya [28] studied the predictive power of crude oil, natural gas, and coal prices in predicting the European carbon price. Vulin et al. [29] used a momentum strategy and a geometric Brownian motion simulation to predict long-term EUA price probabilities. The authors found that carbon price changes are only weakly correlated with coal price changes, but strongly correlated with natural gas. Duan et al. [30], using quantile-on-quantile (QQ) regression and the causality-in-quantiles approach, evaluated the marginal effects of energy prices on carbon price fluctuations in Phase III of the EU ETS.

Wang and Zhao [31] used a Bayesian network to select the most important variables/markets for predicting carbon prices. The authors investigated the impact of the selected markets on the carbon market. They found that natural gas and crude oil directly affect the carbon price, while the S&P500 and the Global Clean Energy Index have an indirect impact. Wu et al. [32] used partial wavelet analysis to investigate the dynamic multiscale interactions between European carbon and Brent oil futures prices. They found a stable relationship between the two markets, with oil leading at medium and low frequencies. Ye and Xue [33] analyzed the impact of news on carbon price returns. Yuan and Yang [34] provided evidence of an asymmetric risk spillover from financial market uncertainty to the carbon market. Gong et al. [7] analyzed spillover effects between carbon and fossil energy markets due to time-varying VAR with stochastic volatility. They found that, in the second phase of the EU ETS, there was a strong spillover effect of coal on the carbon market and, in the third phase, the natural gas market was increasingly important.

Finally, there is related literature that examines the interactions between energy and carbon market volatilities. This literature typically relies on GARCH specifications to assess interactions in conditional variances (e.g., Liu and Chen [35]; Reboredo [36]; Balcilar et al. [37]), or relies on indices from Diebold and Yilmaz [9,10] to quantify volatility spillover effects (e.g., Chulia et al. [38]; Ji et al. [2]; or Wang and Guo [5]). Our work has similarities with some of the studies mentioned above. It is mainly related to Ji et al. [2], Wand and Guo [5] and Tan et al. [6], as we also build part of our study on the connectedness framework of Diebold and Yilmaz [9,10]. However, it overcomes some weaknesses in the existing literature. First, previous studies have typically selected variables in an ad hoc manner or based on expected financial market integration, rather than on proper economic modeling. In contrast, we develop a small, theoretical model for the EU ETS market that provides a framework for building the empirical model.

Second, existing studies based on connectedness indices, such as Ji et al. [2], Wand and Guo [5], and Tan et al. [6], have typically considered prices in (log) differences (returns) and relied on the generalized framework of Pesaran and Shin [39] to deal with correlated innovations. Unlike previous work, we perform the analysis in (log) levels and identify the VAR. On the one hand, considering the level of variables allows us to account for long-run relationships between variables that are lost when analyzing in differences, since differentiation destroys low-frequency fluctuations. On the other hand, the structural identification of VAR allows us to assess the sign of carbon price responses to shocks. Note that the sign of responses to shocks cannot be evaluated in the generalized framework, since by construction each pair of cross-responses in this framework has the same sign.

Finally, we explicitly account for the specific time horizon at which the links between the model variables and the carbon price emerge by calculating indices of connectedness in the frequency domain. Frequency-domain analysis allows us to distinguish between time periods in which high- and low-frequency associations occur. Although this distinction has been neglected in previous studies, it is crucial for understanding the ETS mechanism. When connectedness occurs at high frequencies, shocks are transmitted in short-term movements and have transitory effects on the carbon price. In contrast, shocks that occur at low frequencies have permanent effects on the carbon market. Moreover, frequency-domain analysis allows us to identify the omitted fundamental part of carbon price shocks.

3. Theoretical model

Emission permits are issued by the European Commission and distributed through a single EU registry. For the 2013–2020 trading period (Phase 3), 57% of permits were auctioned, while the rest were distributed for free. At the beginning of the third trading period, the manufacturing sector received 80% of its allowances for free. This share fell to 30% in 2020. Electricity generators have not received free allowances since 2013, at least in principle, but some are still available in several Member States.

As is common in economic modeling, we assume that supply and demand define the carbon price:

$$P_{CO_2} = f\left(\overline{Q}, D_{CO_2}\right), \tag{1}$$

where P_{CO_2} denotes the carbon price and D_{CO_2} the need for permits, reflecting the total emission intensity of the economy. Finally, $\overline{Q}$ is the number of permits available, defined as the total number issued in a particular year minus those distributed for free.[1] As a result, the number of permits $\overline{Q}$ is constant in a year. We split the demand for permits between the two main sectors—electricity generation and industrial processes. Thus, to distinguish between final energy consumption and transformation uses embodied in the ETS scheme:

$$D_{CO_2} = D_{CO_2}^{ELE} + D_{CO_2}^{IND}. \tag{2}$$

Electricity plays an essential role in our model. Although consumption does not generate emissions, electricity production does. [2]Electricity generation may emit more or less CO_2, depending on the share of fossil fuel energy sources used for power generation. The emission cost in electricity generation is transferred to the price and paid by the electricity consumers (Fabra and Reguant, [40]). Natural gas and coal are the primary fossil fuels used for electricity generation in the EU.[3] So, the total demand for permits generated by the electricity sector can be represented as follows:

$$D_{CO_2}^{ELE} = \alpha_{gas} * D_{gas}^{ELE} + \alpha_{coal} * D_{coal}^{ELE}, \tag{3}$$

where α_{gas} and α_{coal} stand for CO_2 emission intensities of natural gas and coal, while D_{gas}^{ELE} and D_{coal}^{ELE} stand for the total demand for these fossil fuels for power generation.

Multiplying and dividing Equation (3) by the total demand for fossil fuels for electricity generation, D_{FF}^{ELE}, and by electricity demand, D_{ELE}, we get: [4]

$$D_{CO_2}^{ELE} = \frac{D_{FF}^{ELE}}{D_{ELE}}\left(\alpha_{gas} * \frac{D_{gas}^{ELE}}{D_{FF}^{ELE}} + \alpha_{coal} * \frac{D_{coal}^{ELE}}{D_{FF}^{ELE}}\right) * D_{ELE} = s_{FF} * \alpha_{FF}^{ELE} * D_{ELE}. \tag{4}$$

where s_{FF} denotes the share of fossil fuels used for power generation and α_{FF}^{ELE} the weighted average emission intensity of fossil fuels used for electricity production. Thereafter, the total CO_2 emissions generated by industrial production can be represented as follows: [5]

$$D_{CO_2}^{IND} = \alpha_{gas} * D_{gas}^{IND} + \alpha_{coal} * D_{coal}^{IND} + \alpha_{oil} * D_{oil}^{IND}. \tag{5}$$

Finally, adding equations (4) and (5), we get the total demand for CO_2 permits:

$$D_{CO_2} = \alpha_{gas} * D_{gas}^{IND} + \alpha_{coal} * D_{coal}^{IND} + \alpha_{oil} * D_{oil}^{IND} + s_{FF} * \alpha_{FF}^{ELE} * D_{ELE}. \tag{6}$$

To summarize, we take the perspective of final energy consumption. We assign positive CO_2 emissions to oil (including petroleum products), coal, natural gas, and electricity. We assume that emission intensities are

[1] For simplicity, we ignore the possibility of using permits issued in year t in subsequent years, which has been possible since Phase 2 (2008), and the possibility of borrowing allowances from a future allocation for one year to meet obligations for the current year.

[2] Electricity demand does not influence permit demand directly as firms that consume electricity do not buy permits.

[3] Although some Member States still use oil for electricity generation, their total contribution is very small and is omitted here as insignificant (1.6% in 2017).

[4] Strictly speaking, D_{ELE} is the energy demand (fossil fuels and clean energy) for electricity production. However, given that electricity production is a way to transform energy, we can assume that the energy demand here is equal to the electricity supply and, in its turn, electricity supply is equal to the electricity demand at a given price.

[5] Consumption of renewable energy for industrial processes is not included in our model because it is still minimal. In 2017, 99.5% of industrial energy consumption comprised coal, natural gas, oil products, and electricity. The latter is especially relevant as its share increased from 28% to 34% in the last 20 years.

fixed for oil, coal, and natural gas, and vary for electricity only through the demand for coal and natural gas for power generation.

Our model also assumes that the demand for any fuel type in (6) is determined by the following fundamental factors: the production level of the economy Y(reflecting the need for industrial production or consumption of manufactured goods), the prices of this fuel, and its fuels-substitutes, and the carbon price. Thus, the demand for CO_2 permits can be rewritten as follows:

$$D_{CO_2} = f\left(Y, P_{gas}, P_{coal}, P_{oil}, P_{ele}, P_{CO_2}, s_{FF}\right) \tag{7}$$

Eq. (7) can be transformed to a linear function by log-linear approximation, where the log-demand for permits is determined by the sum of variables weighted by a factor specifying their importance in (7):

$$\begin{aligned} lnD_{CO_2} = \zeta_1 lnY + \zeta_2 lns_{FF} + \zeta_3 lnP_{oil} + \zeta_4 lnP_{coal} + \zeta_5 lnP_{gas} + \\ + \zeta_6 lnP_{ele} + \zeta_7 lnP^R_{CO_2}. \end{aligned} \tag{8}$$

Similarly, the price of permits in (1) can be expressed as:

$$lnP_{CO_2} = ln\overline{Q} + \mu_d lnD_{CO_2}. \tag{9}$$

The $ln\overline{Q}$ can be considered a yearly mean as it is constant within the year. The parameter μ_d accounts for the relative importance of the demand for permitsD_{CO_2} in price-setting.

To complete the model, we subsume (8) within (9) and solve for lnP_{CO_2}. We account for omitted factors influencing the carbon price by including an error term ε_{CO_2}:

$$\begin{aligned} lnP_{CO_2} = \gamma_0 ln\left(\overline{Q}\right) + \gamma_1 lnY + \gamma_2 lns_{FF} + \gamma_3 lnP_{oil} + \gamma_4 lnP_{coal} + \gamma_5 lnP_{gas} + \\ + \gamma_6 lnP_{elec} + \varepsilon_{CO_2}. \end{aligned} \tag{10}$$

Additional complexity arises in modeling the error term. Carbon allowances have become a financial instrument. Thus, price dynamics are influenced by events with little to do with the underlying economic determinants (for example, some temporary phenomena like sporadic events and psychological factors in the market). Formally, this means that the term ε_{CO_2}in (10) can be decomposed into two unobserved components: $\varepsilon_{CO_2} = \varepsilon^F_{CO_2} + \varepsilon^M_{CO_2}$, where $\varepsilon^F_{CO_2}$ denotes unexpected changes in omitted policy and fundamental factors and $\varepsilon^M_{CO_2}$ denotes unexpected carbon market shocks related to speculation and other microstructure noises.

4. Econometric framework

4.1. Reduced form and structural VAR

Consider a VAR model for a $N \times 1$ vector of variables Y_t , $t = 1,...,T$, where T is the number of observations:

$$Y_t = \left[I - F_p(L)\right]^{-1}\varepsilon_t. \tag{11}$$

The $N \times N$ matrix I is an identity matrix, $F_p(L)$ is a matrix of stationary polynomials of lag p, and $\varepsilon_t \sim N(0, \Omega)$ is a vector of $N \times 1$ reduced form errors.

The structural VAR model is given by:

$$Y_t = \left[I - F_p(L)\right]^{-1} A\xi_t = \Lambda(L)\xi_t, \tag{12}$$

where ξ_t is a $N \times 1$ vector of uncorrelated structural shocks with identity variance–covariance matrix, i.e., $\xi_t \sim N(0, I)$. The elements of the N × N matrix Λ(L) in (12) are infinite polynomials whose coefficients are the impulse responses (IRF) of the structural shocks' variables. The matrix A is the structural matrix relating reduced form and structural shocks $\varepsilon_t = A\xi_t$, therefore $\Omega = AA'$.

4.2. Measures of connectedness in the frequency domain

To analyze the contributions of shocks at different frequency ranges (short-run, medium-run, and long-run), we compute connectedness measures based on the spectral decomposition of the VAR variance, as proposed in Barunik and Krehlik [11]. Note, however, that these authors base their indices on a reduced form VAR and rely on the generalized framework (Pesaran and Shin [39]) to deal with correlated innovations. Unlike them, we employ a structural VAR (SVAR), and identify the structural shocks that allows us to determine the sign of the responses to shocks.

The causation spectrum of the structural VAR process in (12) at a frequency ω is defined by

$$f_{j,k}(\omega) = \frac{\left|\left\{\left[I - F\left(e^{i\omega}\right)\right]^{-1} A\right\}_{j,k}\right|^2}{\left\{\left[I - F\left(e^{i\omega}\right)\right]^{-1}\Omega\left[I - F'\left(e^{-i\omega}\right)\right]^{-1}\right\}_{j,j}},$$

where $i = \sqrt{-1}$ is the imaginary unit, $F\left(e^{i\omega}\right) = Fe^{i\omega} + Fe^{2i\omega} + ... + Fe^{pi\omega}$ and $F'\left(e^{-i\omega}\right)$ is a complex conjugate transpose of $F\left(e^{i\omega}\right)$, $\omega = \frac{2\pi j}{T}$, $j = 1, ..., \frac{T}{2}$. Consider a frequency range$d = (a, b) : a, b \in (-\pi, \pi), a < b$. The spectral decomposition at the frequency band d is defined as:

$$f^d_{j,k} = \int_a^b f_{j,k}(\omega)d\omega, \tag{13}$$

where the integral can be approximated by summation over Fourier frequencies belonging to the selected range.

The magnitude $f^d_{j,k}$is the index of *pairwise within connectedness* at the frequency range d. It measures the portion of the variable j-th fluctuations within the selected range due to the k-th structural shock. This index can be summed for all $k \neq j$ to get *directional within connectedness* FROM others at the frequency range, which measures the share of the variable j fluctuations within the band due to all other structural shocks:

$$f^d_{j\leftarrow\bullet} = \sum_{k=1,k\neq j}^{N} f^d_{j,k}. \tag{14}$$

Note, however, that *within connectedness* indices do not account for the relative importance of the selected frequency range. Barunik and Krehlik [11] pre-multiply the causation spectrum by a weighting function reflecting the power of the j-th variable at a frequency ω:

$$\Gamma_j(\omega) = \frac{\left[\Lambda\left(e^{i\omega}\right)\Omega\Lambda'\left(e^{-i\omega}\right)\right]_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left[\Lambda\left(e^{i\lambda}\right)\Omega\Lambda'\left(e^{-i\lambda}\right)\right]_{j,j}d\lambda}$$

and compute *pairwise frequency connectedness* as:

$$\Theta^d_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega) f_{j,k}(\omega)d\omega. \tag{15}$$

Pairwise frequency connectedness measures the relative importance of variable j-th fluctuations at the selected band generated by the k-th structural shock in the total j-th variance. This index also can be extended to *directional frequency connectedness* FROM all other variables on a frequency band as:

$$\Theta^d_{j\leftarrow\bullet} = \sum_{k=1,k\neq j}^{N} \Theta^d_{j,k} \tag{16}$$

Consider a partition of the whole spectrum space into s bands $d_s, \forall s$ satisfies the following conditions: $\bigcap d_s = \varnothing$ and $\bigcup d_s = D$, then

$$\Theta^D_{j,k} = \sum_s \Theta^{d_s}_{j,k} \tag{17}$$

As Barunik and Krehlik [11] show, $\Theta^D_{j,k}$is the standard Diebold and Yilmaz [9,10] pairwise (time-domain) connectedness, which measures the contribution of the k-th structural shock to the overall j-th variable variance.[6]

5. Empirical model

In this section, we build an empirical SVAR model consistent with the theoretical formulation in Section 3.

5.1. Data description

For the variables in the model, we have chosen the following approximations, which we believe are representative at the EU level. We do not exclude the UK from the analysis as it has been part of the EU energy system and the EU ETS throughout the period covered by our model.

For the prices of fuels, we employ the first monthly futures of publicly traded contracts: Brent crude oil contracts for P_{oil}, Rotterdam coal contracts for P_{coal}, Title Transfer Facility (TTF) gas contracts for P_{gas}, and German electricity base contracts as a proxy for European P_{ele}.[7] In addition, we take the first-month future contract for P_{CO2}.[8] We use futures contracts because they are less affected by short-run noise than the spot and are more actively traded (Sadorsky [41]). Besides, most studies on connectedness in different markets use futures prices. For the economic output variable, we use the economic activity index STOXX for the EU. Inspired by Kilian [42], we also use the Baltic Dry Index as a robustness check.[9] Renewable electricity share data is collected at the EU level, monthly, and taken from Eurostat.[10]

The data sample runs from the first week (7–13 of January) of 2008 to the 39th week (24–30 of September) of 2018. The starting point is restricted by the availability of data on renewable electricity share. Data plots can be found in the on-line Supplement. As in Kilian [42,43], or Hammoudeh et al. [26], we employ the log-level specification for the VAR because it allows us to investigate long-term association between variables, which is lost if the data is considered in first differences. We collect all variables in a vector X_t:

$$X_t = [lnsFF_t, lnY_t, lnP_{oil,t}, lnP_{gas,t}, lnP_{coal,t}, lnP_{ele,t}, lnP_{CO_2,t}], \tag{18}$$

Some of the variables require additional transformations to match the theoretical model. For example, according to Eq. (11), the carbon price is affected by demand factors and by the supply of allowances, which is constant in a given year. However, the short data span available does not allow us to quantify the importance of supply shocks. Consequently, we focus on quantifying demand-side effects only. To do so, we subtract the yearly mean from carbon permit prices. In this way, we account for year-specific effects resulting from changes in the supply of allowances and other specific annual factors.[11] Also, we seasonally adjust the share of fossil fuels in electricity production, s_{FF}, and we produce interpolation of the observations inside a month by linear projection. Details on the model specification and the data transformations are available in the on-line Supplement.

5.2. Identification restrictions

Structural shocks in the SVAR are conceptually defined as shifts in the corresponding model variables that the model cannot anticipate. We identify the VAR placing zero contemporaneous restrictions on the variables, as in Kilian [42,43], and Hammoudeh et al. [26]. More specifically, we assume that variables situated above in the vector X_t are not contemporaneously affected by variables located below; that is, the structural matrix A in (12) is lower-triangular. Thus, the variables in (18) have been ordered accordingly, placing fewer contemporaneous restrictions on more reactive (agile) variables.

The first variable in (18) is s_{FF}. Since this variable is only available monthly, it seems reasonable to assume that unexpected weekly changes in prices or activity cannot influence it contemporaneously. The installed power capacity from renewables is also fixed in the short run as it requires time to be built. That is why renewable generation is limited in the short term, and we can only expect to see the impact of the carbon price in the medium to long term. The order of the remaining variables in the VAR follows the same logic. For example, economic activity is assumed not to respond contemporaneously to energy and carbon price, although shocks to activity can influence prices on impact. Also, we allow gasoline and coal to respond to contemporaneous shocks to the more global oil market but not to the more local electricity market. We do not place contemporaneous restrictions on the CO_2 market because this variable can be contemporaneously affected by all other variables according to Eq. (10). Consequently, the carbon price is conveniently ordered last in the vector (18).

Notice that the last Equation of the SVAR can be interpreted in terms of our theoretical model as Eq. (10) augmented with lagged variables. However, in Eq. (10), the CO_2 market-specific shock is split into two components, i.e., $\varepsilon_{CO_2} = \varepsilon^F_{CO_2} + \varepsilon^M_{CO_2}$. The first component collects the reaction of the carbon price to changes in omitted policy and fundamental variables. The second component accounts for unexpected changes in the speculative demand for permits. Given that these two shocks are not separately identified in the SVAR, we employ a spectral variance decomposition to isolate their effects. We assume that unexpected changes in the speculative demand for permits have relatively short-lived effects—at most half a year, although they typically vanish in one month or less. Therefore, the long-run effects of the CO_2 market-specific shock represent changes in omitted policy or fundamental variables. This type of identification allows us to assess the importance of speculation and other market-specific factors in CO_2 pricing.

5.3. Estimation strategy

We follow the standard practice of estimating the VAR over a rolling window, to account for possible changes in the parameters, by adding and removing one observation each time that we move the window. The length of the window corresponds to $T = 156$ points (approximately three years).[12] According to Akaike and Schwarz criteria, we allow for

[6] This identity holds in the long run. However, it also valid for finite forecast horizons as far as these are not too short. For example, we find that pairwise connectedness computed from time-domain formulas deliver the same numbers using the typical H=10 ahead horizon.

[7] Germany is chosen because it is interconnected with other MS of different geographies (covering North and East Europe). Also, Germany's generation mix is typical of the EU's. Weekly data was collected through Thompson Reuters Eikon platform, contracts *LCOc1*, *TRNLTTFMc1*, *ATWMc1*, *TRDEBMc1*.

[8] Secondary market price is used to approximate the whole EU market. Also, future prices are only available on the secondary market. Weekly data was collected through Thompson Reuters Eikon platform, contract *CFI2Zc1*.

[9] STOXX and Baltic Dry weekly data was collected through Thompson Reuters Eikon platform.

[10] Monthly data is available in the "Eurostat nrg_150m" database.

[11] Note that the approach is equivalent to employing yearly dummies in a static framework. The use of dummies is not appealing in the dynamic framework because the estimated dummy for a non-full year in the sample changes depending on the number of observations. Subsequently, they would be strongly influenced by the sample-specific effect, introducing noise to the year-specific effect we aim to subtract..

[12] We repeat the estimation with T=208 (approximately four years). The main results are robust to the change of the window. Results are available on request.

four lags in the autoregressive part.

Frequency connectedness is evaluated at three ranges: high frequencies, with a period from one to four weeks (one month approximately), medium frequencies, with a period from five to 26 weeks (from one month to half a year), and low frequencies (periods of more than 26 weeks). The boundary for the low-frequency band is set with the idea that all speculative market-specific noises are absorbed and "digested" by the market within half a year. Thus, the remaining frequencies correspond to fundamental factors only.

6. Empirical results

This section presents the empirical results for the CO2 equation. The purpose of this analysis is to examine the extent to which changes in the fundamentals of carbon demand explain the recent increase in the price of carbon.

6.1. Aggregated connectedness FROM model variables

The solid black line in Fig. 1 is the index of directional connectedness FROM all model variables to the carbon price (CO2FROM). This index quantifies the extent to which fluctuations in the carbon price are explained by shocks to the other variables in the SVAR. These variables are the main drivers of the demand for CO2 allowances in the theoretical model (see Eq. (10)). In this sense, CO2FROM reflects the explanatory power of the model.

On average, the shocks to the model variables explain 65% of the variance in the carbon price, which is a high percentage for weekly data. However, we find substantial differences across subsamples. The index alternates between periods with relatively high connectedness, as in the second quarter of 2017, when CO2FROM reaches 90%, with others where the connectedness is relatively low, as in the first quarter of 2015, when shocks to fundamental variables explain barely 30% of the carbon price variance. The average value of the index since mid-2018 is 85%, which means that our model can explain a large proportion of recent fluctuations in the carbon price.

Fig. 1 also decomposes the CO2FROM index into its short-, medium-, and long-term components. These components quantify the percentage of the total variance in the carbon price that is transmitted by other model variables in high-, medium-, and low-frequency ranges. As the figure shows, the long-term component accounts for most of the uncertainty transmitted. Shocks to the explicative variables in the model thus have primarily long-term effects and create a favorable environment for policy interventions. However, this result does not mean that the fundamental variables in the model are not significant drivers of carbon price fluctuations at higher frequencies. Their importance at these frequencies may not be reflected in Fig. 1 because the carbon price is very persistent and the low-frequency fluctuations account for most of the variance.

To shed light on this issue, Fig. 2 presents the directional within connectedness FROM model variables at the three selected ranges. Directional connectedness quantifies the importance of transmitted shocks to carbon price fluctuations in a given frequency range. As Fig. 2 shows, transmission explains most of the carbon price fluctuations at low frequencies. Although the corresponding share is not negligible at higher frequencies, it is much smaller (25% on average). This result suggests that short- and medium-term carbon price fluctuations are mainly a consequence of carbon market shocks.

It is also important to note that the CO2FROM index shown in Fig. 1 is considerably larger than the corresponding index in Ji et al. [2] and Wang and Guo [5]. These two studies conclude that carbon price fluctuations are primarily explained by their own shocks, with the index of directional connectedness ranging from 15% to 35%, depending on the period. Our estimated values are higher because we produce analysis in (log) levels, while the prices in these two studies are (log) differenced. As mentioned earlier, differencing destroys low-frequency fluctuations. Their analysis therefore neglects the significant contribution of the model variables to low-frequency fluctuations of the carbon price, i.e., the range that contributes most to the total variance. However, their results are consistent with within connectedness indices at medium- and high-frequency ranges in Fig. 2. It can be shown that an aggregate of these two indices, weighted by the relative importance of each range to the total high- and mid-frequency variance (and thus omitting low-frequency movements), is similar to the directional connectedness of other variables in Ji et al. [2] and Wang and Guo [5].

Overall, our results indicate that the model in Section 3 explains carbon price fluctuations well. The variation in model variables explains a high proportion of the variance, especially at low frequencies and after mid-2018. The effect of the own shock is reasonably limited and concentrates, mainly, at high and medium frequencies, which have less importance in the total variance. We consider these issues further in the next section, where we discuss the importance of each variable in carbon price fluctuations, including CO_2 market-specific shocks.

6.2. Pairwise connectedness analysis

Fig. 3 shows pairwise indices of connectedness from each fundamental to carbon price to further explore the transmission determinants. The pairwise indices quantify the percentage that each variable explains of the carbon price variation and add up to the CO2FROM index in Fig. 1 when aggregated across all variables.

We also evaluate pairwise connectedness by frequency ranges. We do not report the decomposition of the pairwise indices into their short-, medium-, and long-term components because the long-term component accounts for almost all the corresponding indices, as in Fig. 1. However, Fig. 3 shows the pairwise connectedness within each frequency range. The figure also shows the sign of the carbon price response to structural shocks, which provide additional insights into the functioning of the permit market system over time. In Fig. 3, the subsamples in which a (positive) structural shock increases the price, at least in the first four weeks, are highlighted in blue. Red areas highlight subsamples in which the positive shocks to the fundamental variables cause the carbon price to decline over the same period.

As Fig. 3 shows, there are two identifiable periods in terms of the sign of the carbon price response to a shock in the share of fossil fuels in electricity generation. Contrary to economic intuition, the sign prior to 2016 is predominantly negative, implying that an unexpected increase in the share of fossil fuels in electricity generation has a negative impact on the carbon price.[13] From 2016, however, the sign turns positive, as the theory predicts. Its overall importance on carbon price fluctuations is moderate. We find a spike in connectedness around 2014, a likely consequence of the oversupply of permits. Economic activity was below 2011 levels, and some permits were still allocated to electricity plants for free (recall that the carbon price has a reversed sign in this period). However, the index barely reaches 10% in recent years, where the carbon price response has the expected sign. One possible explanation is that the share of fossil fuels in electricity generation is exogenously determined by the electricity generation capacity mix, which has not changed dramatically in recent years. While electricity producers are slowly moving away from fossil fuels, they still use them more when RES production falls or electricity demand rises.

Shocks to s_{FF} contribute primarily to low-frequency fluctuations, especially when connectedness with the carbon price is high. In

[13] The negative relationship between the S_{FF} and the carbon price in 2013–2016 probably indicates that the entry of electricity generation into the ETS destabilized the carbon market for several years. Electricity generation was not part of the ETS until 2013. Its introduction probably had a dual effect of increasing demand for allowances and encouraging investment in renewable electricity generation. Our results show that these unsettling effects stopped in 2016.

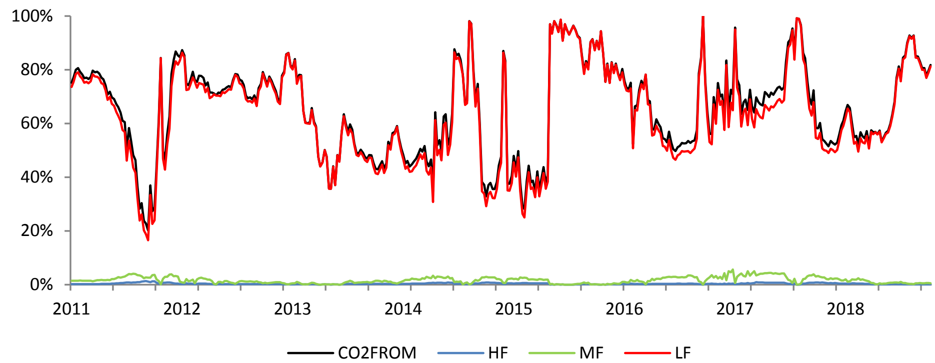

Fig. 1. Directional connectedness FROM all model variables to the carbon price variance and its decomposition into the high- (HF), medium- (MF), and low-frequency (LF) components.

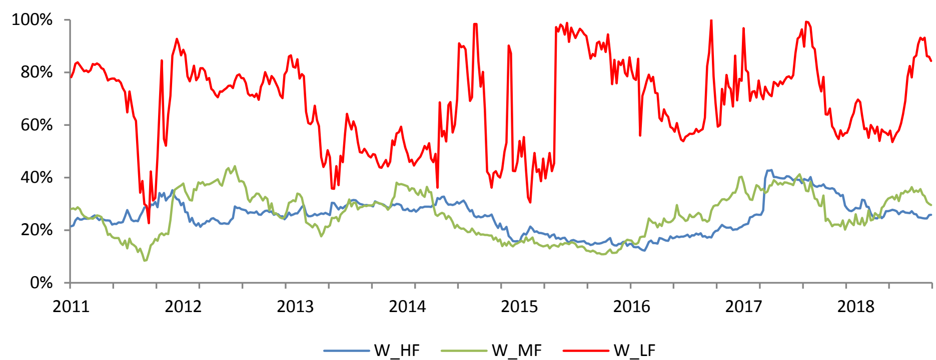

Fig. 2. Within connectedness FROM all model variables to the carbon price fluctuations at high (W_HF), medium (W_MF), and low frequencies (W_LF).

2016–2017, it also contributed significantly to mid-frequencies, coinciding with the expected sign of the carbon price response. However, its contribution at high frequencies is negligible, which is consistent with the monthly frequency of the available data.

As expected, shocks to economic activity are positively associated with the carbon price, especially from 2016 onwards. Economic growth implies higher demand for fossil fuels and hence higher demand for carbon credits. As Fig. 3 shows, economic activity has always been one of the main drivers of carbon price fluctuations. Its average contribution is 10%, although in some periods the percentage is significantly larger, such as in 2012 and 2015 (40%). However, since 2016, the importance of this activity has decreased significantly and is currently responsible for only five percent of the total carbon price fluctuations. Our results therefore show a progressive decoupling of the carbon market from economic activity, which is consistent with the recent emission-output independencies in EU countries stressed in the literature (see, e.g., Cohen et al. [44]; Wu et al. [45]).[14] As for the frequency band, economic activity contributes more at low frequencies, with shocks having persistent effects on the carbon price. Its contribution to high-frequency movements is also relatively high, albeit negligible nowadays. Although oil and refined petroleum products generate emissions, their use in EU countries is mainly concentrated in the transport sector, which is not (yet) subject to the ETS. Nevertheless, we include the oil price in the model because it reflects two factors simultaneously. First, it is traditionally a good indicator of the long-term price of natural gas, as indexation of the gas price to the oil price has been common in Europe since the 1960 s. Although oil indexation has declined, many long-term gas contracts are directly or indirectly linked to the oil price. The second reason is that the oil price reflects a global component of the energy system, as it is the most traded commodity in the world.

Consistent with both reasons, we find that a positive oil price shock is associated with a higher carbon price. On average, oil price shocks account for about 20% of the variation in the carbon price. However, the importance of oil is more pronounced in the second half of our sample. It started with an intense connectivity episode in 2015–2016, after the oil price drop caused by the huge oil glut. The information transmitted by this market has long-term effects on the carbon price, supporting the idea that the oil price reflects a global component of the energy system.

The natural gas shock is associated with a rise in the price of carbon, as the theory predicts. A rise in the price of natural gas gives the nearest substitute fuel, coal, a competitive advantage and increases its demand. Since coal emits more CO2 than natural gas, substitution incentives increase the demand for permits and the carbon price. Our empirical results support these predictions, especially in the latter part of the sample. Overall, natural gas hub price fluctuations explain up to 50% of carbon price fluctuations in 2011–2015 and up to 30% from mid-2016. Moreover, we observe a massive decline in pairwise connectedness in 2015–2016, consistent with the increasing importance of oil prices in this period. Pairwise within connectedness indices signal the importance of the gas market in the low-frequency fluctuations of the carbon price. This index reaches a value of 20% in 2014, making the gas market the main contributor to fluctuations in this frequency range. The increasing importance of the gas market from the third phase of the EU ETS is also documented in Gong et al. [7].

Consistent with the results for natural gas, positive shocks to coal prices are associated with a decline in the carbon price. The higher the coal price, the greater the incentive to substitute natural gas for coal. Coal-specific shocks did not explain more than 10% of the variation in the permit price until 2016; however, they explained significantly more thereafter, with strong peaks in connectedness in mid-2017 and mid-

[14] The result is stable if the Baltic Dry Index is used instead of STOXX index as in Kilian [42].

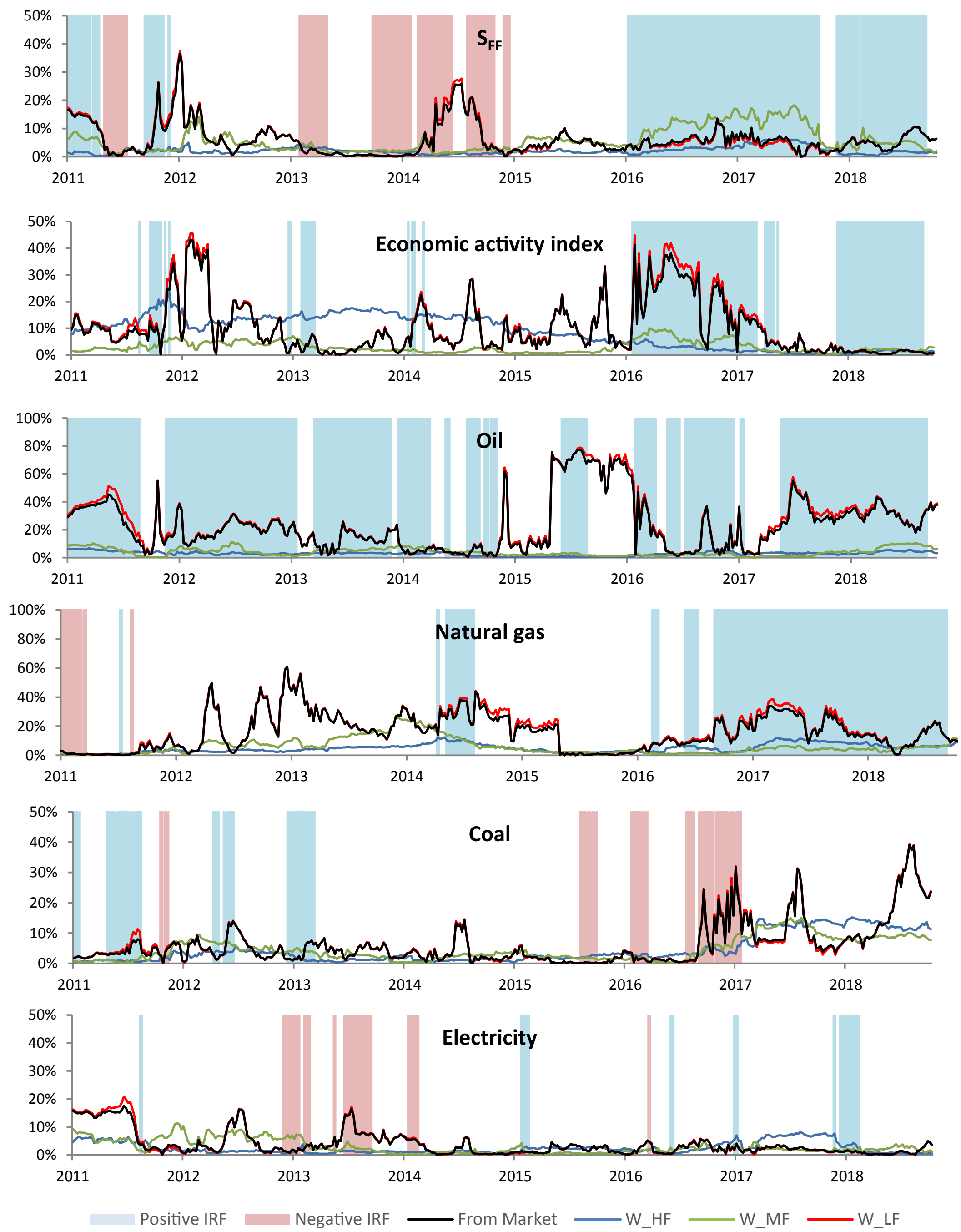

Fig. 3. Pairwise and pairwise within connectedness from each model variable to the carbon price together with the sign of the response of the carbon price to each structural shock.

2018, likely a consequence of the shortages generated by stringent environmental regulations. As with the other fundamental variables, coal price shocks are more important for low frequency fluctuations. However, it is important to emphasize that coal price shocks are also responsible for a relatively significant share of higher-frequency carbon price fluctuations from 2017 onwards, when other climate policies provide an additional incentive to move away from coal in addition to rising carbon prices.

As for electricity market shocks, these have an undetermined effect on the carbon price. However, their overall importance is minimal, especially from 2014. Note that the connectedness episodes have almost disappeared from the start of Phase 3 in 2013, where free allocations for electricity generation were eliminated. CO2 permits, together with fossil fuels, are inputs for electricity generation. This is the reason why the carbon price directly impacts electricity prices and not vice versa. However, there are also two indirect channels. First, electricity and CO_2 markets are closely related, suggesting expectation synergies, and that is why electricity price has more importance in explaining the high-frequency variance of carbon prices. Second, electricity price shocks could influence the carbon market before Phase 3 through electricity and fossil fuel demand (as substitutes or complements for industrial products). This indirect channel disappeared in 2014 when electricity facilities fully assumed the CO_2 costs of their generation.

We complement the analysis by assessing the contribution of carbon market shocks. These results are presented in Fig. 4. Since the shocks were normalized as positive, the CO2 shock increases carbon prices by

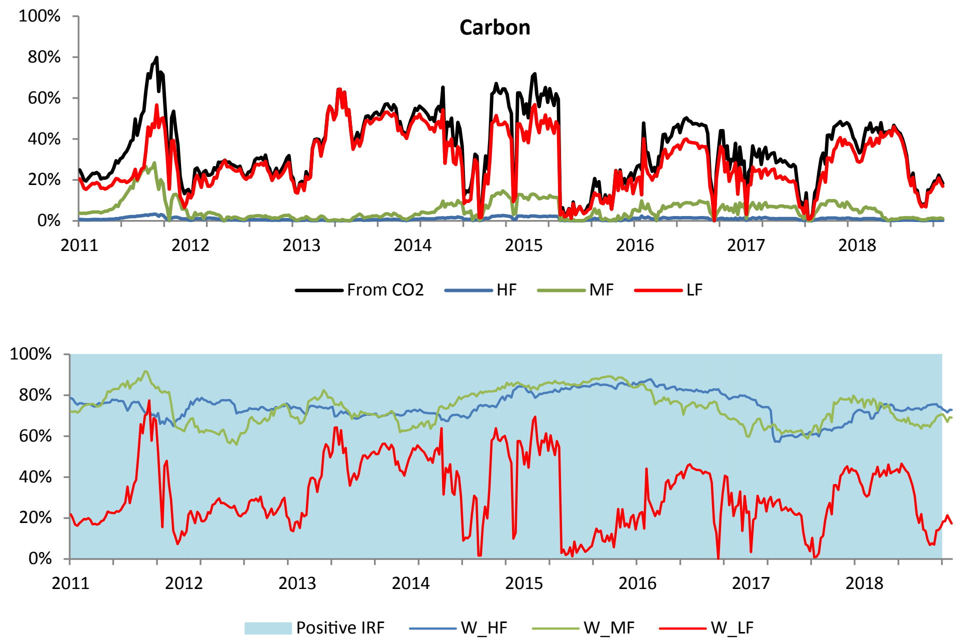

Fig. 4. Contribution of the own carbon market shock to carbon price. The first panel shows the percentage contribution to variance and its decomposition into high (HF)-, medium-(MF), and low-frequency (LF) components. The second panel depicts its contribution within the specific ranges (W_LF, W_MF, W_LF).

assumption. The first panel of Fig. 4 shows the percentage contribution of the carbon market shock along with its decomposition into short-, medium-, and long-term components. This shock accounts for about 35% of the total carbon price fluctuations across subsamples (i.e., the share not explained by other shocks in the model). However, its share has decreased substantially since mid-2018. According to our identification proposed in Section 5.3, the long-run effects reflect policy channels and underlying variables that are not included in the model. In contrast, the medium- and especially the short-run effects result from speculative shocks and microstructure noise in the CO2 market. As the figure shows, the low-frequency fluctuations are responsible for most of the carbon price variance. Thus, speculation and other microstructure noise in the carbon market are not the main drivers of carbon price fluctuations.

However, the above result does not mean that speculation in the carbon market is not important. To illustrate this, the second panel of Fig. 4 plots the contribution of the CO2 shock in each frequency range. In contrast to the shocks in the fundamentals, the CO2 market shock explains a substantial fraction in the mid- and high-frequency ranges (about 80% on average). Thus, our results show that almost all the mid- and high-frequency swings in the carbon price are mainly due to speculative shocks. Although these fluctuations do not account for a large share of the total variance of the carbon price, they are crucial for specific agents, such as short-term investors, as their trading horizon is only affected by high-frequency fluctuations.

7. Implications and concluding remarks

This paper developed a theoretical model linking the energy sector (oil, natural gas, coal, electricity prices, and the share of fossil fuels in electricity generation), economic activity, and the carbon market. The model was empirically represented by a structural VAR estimated dynamically with a moving regression window. Based on the dynamic estimates, we quantified the impact of each model variable on the carbon price over time using impulse response analysis and connectedness measures based on frequency-variance decompositions.

In this regard, related literature has provided limited evidence on the horizon at which information is transferred from other markets to the carbon price. We shed light on this issue by assessing connectedness across different frequency ranges. Frequency-domain analysis has allowed us to disentangle the specific frequencies at which linkages arise. This knowledge is essential for understanding the carbon market, as the implications for carbon price dynamics vary depending on the frequency at which information is transmitted. Thus, if the information is mainly transmitted at high frequencies, its effects on the carbon price are transitory and fizzle out in the short run. On the other hand, if the information is transmitted at low frequencies, the effect on the carbon price is persistent. Frequency domain analysis has also allowed us to identify the impact of omitted policy and fundamental variables from speculative and microstructural noise on the carbon market shock.

We show that the fundamental variables included in the model explain most of the observed variance of the carbon price adjusted for supply effects, but with substantial differences across subsamples. Nevertheless, the percentage has increased nowadays, suggesting that the ETS has recently started to work properly. This view is supported by the theoretically consistent responses of carbon prices to shocks in the recent subsamples. Nevertheless, unaccounted EU policy changes in ETS markets might have supported the considered demand forces in determining the carbon price, as the carbon market shock explains a non-negligible part of the fluctuations. However, it is difficult to separate its effects conceptually or quantitatively from other underlying variables not considered that may also affect the price. We have also found that shocks from demand-side variables primarily cause low-frequency fluctuations in the carbon price, while speculative shocks to the carbon market are the most important factor in explaining its high-frequency movements.

Our results also suggest that the main drivers of uncertainty have changed over time. In the past, economic activity and natural gas hub prices were responsible for most of the variation in the carbon price. However, their role has diminished, favoring other variables such as oil and especially coal. Moreover, our results suggest that EU countries are succeeding in decoupling production from emissions. These results have important implications for several market participants. In this respect, the indices in the frequency domain are particularly important as not all carbon market players are equal. The uncovered, strong, low-frequency linkages from fundamental variables may be of interest to policymakers as they create a favorable environment for policy interventions. They may also help organizations manage pollutant emissions through environmental programs. In contrast, participants with preferences for shorter time horizons, such as short-term investors, may be more interested in medium- and high-frequency connectedness to manage portfolios and hedge against risks.

For example, the strong linkages between fossil fuels and carbon prices enable policymakers to predict future carbon price fluctuations in different scenarios of fossil fuel price evolution. As fossil fuels shocks have persistent effects on the carbon price, policymakers can evaluate different options for market reforms to help the EU carbon market function well. According to our findings, the oil, gas, and coal markets contribute the most to carbon price variations and are the most effective candidates to influence ETS prices.

Moreover, the evolving relationship between the index of economic activity and carbon prices is an indicator of how "green" current economic growth is. Our results suggest that EU countries are gradually decoupling the carbon market from economic activity. This result is critical in the current economic recovery scenario after COVID, as many governments prioritize economic growth. The finding is also relevant in the current context of further development and improvement of the ETS design announced as part of the European 'Fit for 55′ package. It is expected that the total number of allowances will decrease more rapidly, that fewer free allowances will be given to installations and that several new sectors will be added to the scheme (maritime, road, and buildings). It is therefore important to understand whether the adoption of these new rules will dampen economic activity.

Some of our results also have interesting financial implications, as the CO_2 market is becoming largely financialized. For example, we show that the carbon price is strongly linked to oil and natural gas. However, these markets mainly contribute to the long-run fluctuations of the carbon price, but not its high-frequency movements. As we have shown that the relationship between these two commodities and the carbon price is direct, our results imply that long-term investors in the carbon market are subject to substantial risk from the oil and natural gas markets. For short-term traders, however, this risk is considerably lower, as the influence of these two commodities at high-frequency fluctuations is very small. We show that uncertainty at high- and medium frequencies mostly comes from speculative shocks in the carbon market. Notice that although these shocks have little weight in the total carbon price variance, they matter enormously for short-term traders as their decision horizon is only affected by these frequencies.

Overall, the model represents a virtuous monitoring tool for carbon price dynamics, highlighting the most important vulnerabilities of the emission trading system in real-time, pointing out the potential channels to strengthen it through adequate policies. Moreover, the methodology applied is relatively simple and has been used extensively in economic and financial studies. However, like all empirical work, our study is subject to several shortcomings. The most important, in our opinion, is the limited span of the data, which does not allow us to quantify the importance of permit supply shocks to the carbon price. We have overcome this problem by focusing on demand-side effects only. Other potential concerns, such as the robustness of the choice of some variables or the rolling window length, have been considered explicitly in the text.

This paper has concentrated our attention on the effects of fundamentals and carbon market shocks on the carbon price. However, the empirical framework can also provide information on the likely impact of the carbon price on other variables such as economic activity or fuel prices, which are of great interest to both EU and international stakeholders. An attractive extension might focus on the effect of the model's variables on the share of fossil fuels in electricity generation, a magnitude that has received minimal attention in the literature. We consider these issues to be exciting avenues for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117903.

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