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The Determinants of CO2 prices in the EU ETS System

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Abstract

European Union has launched its Emissions Trading Scheme (ETS) in 2005, creating the first and one of the biggest international carbon markets, with the aim of reducing CO2 emissions of the Member States. Forming a part of the EU Climate Action plan, composed by a broad set of policies, as well as belonging to a complex interrelated energy system, the assessment of the ETS system effectiveness is not straight forward. Policy-makers tend to use emission levels or CO2 prices as indicators, even though both measures are affected by other policies, energy market fundamentals, and speculative shocks. This paper develops an empirical VAR model that connects the energy sector (oil, natural gas, coal and electricity prices, as well as a share of fossil fuels in electricity production), economic activity and CO2 permit prices. We use frequency domain analysis to study how the parts of this system impact each other and how these impacts evolve over time. The model can be used as a monitoring tool for CO2 price dynamics and for the effectiveness of the ETS system. Our empirical results indicate that up to 90% (65% on average) of the variation in CO2 prices, adjusted by supply effects, is explained by the variations in fundamental market variables; however, the individual contributions of them have changed over time. For example, the importance of the economic activity, used to be a major source of CO2 price variations in the past, is vanishing recently, while the opposite occurs to the coal prices, which have gained in importance in recent periods. The impact of CO2 prices on a share of fossil fuels in electricity production is limited, pointing towards the still low contribution of the ETS system for renewable energy penetration.

1. Introduction

European Union has created the Emission Trading Scheme (ETS) system 14 years ago as a part of its climate action plan. It consists of limiting the number of CO_2 allowances and selling them via auction to the eligible emitting entities. In this way, the price is put on CO_2, and if it is high enough, some industrial installations may find it cheaper to change their technology by implementing energy efficiency initiatives or switching to alternative fuels associated with lower CO_2 emissions than to continue paying for CO_2. Moreover, the installations with the cheapest cost of such change will do it first, even when the prices of CO_2 emission permits (CO_2 prices, henceforth) are moderate, and the more expensive do it later, when the prices are higher, contributing to the economic efficiency of emissions reduction path.

The ETS system design relies on market forces, EU establishes and limits the supply, while the market sets the demand, and the price is determined as a consequence of the interaction between supply and demand. For many years the system has been claimed not to be working properly, as it has failed to produce prices high enough to induce technological change towards cleaner production. Recently, the CO_2 prices have more than tripled, reaching 25.7 EUR/ t as of the 23rd of October 2019. The main causes for such a dramatic change are attributed to EU policy decisions, namely removal of extra rights for the year 2019 and enacting more aggressive quantity reduction since 2021.

The press has announced that the European CO_2 market is finally doing its job, praising EU decisions described earlier, as in recent Bloomberg article[1].

[1]The article available online at: *https://www.bloomberg.com/news/articles/2018-03-26/europe-s-38-billion-carbon-market-is-finally-starting-to-work*

But CO_2 prices are determined not only by EU policy concerning the number of permits. Energy and CO_2 prices, demands, efficiencies, and economy are interconnected in a complex system, which represents the demand side of the market. That is why the price of CO_2 permits simultaneously influences and is being influenced by the rest of the factors present in the energy system. Actually, once the path for CO_2 quantities available to the market is set, it is only the demand side who decides on the price, being possible the case when the demand fails to deliver prices high enough for switching to alternative fuels. The occurrence of such situations jeopardizes technological change and achievement of climate action goals, as it has happened in 2010 as the result of the global financial crisis.

Even though the allowances price serves as an indicator of the ETS mechanism effectiveness, monitoring CO_2 price alone does not provide enough information on the success of the market. If CO_2 prices are rising not entirely because of the ETS-related reasons, but at least partially due to energy prices dynamics or renewable energy policies and incentives given by the Member States, this still would be a good result, which, however, would leave the EU out of control when the so-called market forces push in the opposite direction.

A proper indicator of whether indeed ETS market is functioning well or not would be to study how renewable energy penetration reacts to the changes in CO_2 prices. Moreover, it is important to understand how fast this variable reacts to changes in prices of allowances and how long these effects last, separating this from the effect of all other external factors, such as changes in fossil fuel prices.

This paper develops an empirical VAR model which connects energy sector, economic activity, and CO_2 emission prices and allows to study in detail how each element of this system impacts others. There are two main aims of this analysis. First, this model allows for better understanding of what drives CO_2 prices in short, medium and long run, distinguishing between supply and demand effects. The model is a useful monitoring tool for price dynamics of allowances and may help in preparing an efficient toolkit for correcting the CO_2 price, taking into account market forces. This knowledge also would help to timely detect systematic deviations from the desired CO_2 prices path due to demand fluctuations. In this way, policymakers would be able to anticipate a market failure (rather than correct it ex-post) and calibrate a timely signal for the need to adjust the number of permits, or other related policy.

Second, our model makes possible to evaluate the effectiveness of the ETS system by looking at the response of the renewable power share as well as the reaction of our economic activity variable to shocks in CO_2 prices. The model can be used to measure the impact of carbon prices on the economy, in terms of its “cleanness” and growth, as well as to see how fast these impacts appear and propagate.

To answer these two questions we need frequency domain analysis, as the effects on “cleanness” and economic growth are likely to manifest themselves only in the medium and long run because of the minimum necessary time for investments and construction to take place, and cannot be measured otherwise. However, given strong financialization of the market, the short term dynamics, more related to speculative shocks, should not be ignored.

The paper is organized as follows. Section 2 contains the literature review, outlining previous evidence on the determinants of CO_2 prices and discusses previously used methodologies and highlights the main difference of our work with the existing in the literature. Section 3 presents a theoretical model of the energy market, where CO_2 prices interact with the other fundamental variables of the modern energy system. The Econometric framework is presented in Section 4. Section 5 builds the empirical model and discussed the econometric strategy, followed by the discussion of the results in Section 6. Section 7 concludes.

2. Literature review

The review and the analysis of EU ETS market development is produced by European institutions, preparing different types of reports, and by scientific literature studding interaction between variables in complex systems.

Every year the European Commission issues a report on the functioning of the European carbon market. It usually covers recent policy development, number of permits issued, auctioned and distributed for free, and also their split between different types of installations. The report also monitors overall ETS emission levels, but does not provide detailed information or analytics on the prices of permits nor their determinants. Other unofficial reports, such as 2019 State of the EU ETS Report by ERCST, do report on ETS market functioning using indicators such as volumes, open interest, auction participations, auction coverage, auction vs spot spread, bid-ask spread, cost of carry and volatility.

The EU ETS has attracted a lot of attention in the analytical literature from the first years the data become available. Mostly, the studies examine the main drivers of the carbon prices or the dynamic relationship between carbon and other markets. Both questions are closely interrelated since the financial integration between markets makes it very difficult to identify which market is playing the role of driver and which one is the follower.

In the early research, it is possible to find papers on purely time series modelling of the price dynamics of CO_2 emission allowances (see among others the works of Paolella and Taschini (2008), Benz and Trück (2009) and Daskalakis et al. (2009)). However in this period, the authors mostly study the main determinant of the carbon prices. Thus, Christiansen et al. (2005) suggest that market fundamentals, such as weather, fuel prices, and fuel switching, policy and regulation play important role in carbon prices determination. In the subsequent studies (see Mansanet-Bataller et al. (2007), Alberola et al. (2008), Keppler and Mansanet-Bataller (2010), Hintermann (2010), Chevallier (2011), Creti et al. (2012), Aatola (2013)) the authors conclude that fuel price is one of the most important determinants of the carbon price. Most of these authors agree that the economic activity indicator is important driver of EUA prices, and some of them use a stock market index as an indicator for economic activity. For the early period of carbon prices modelling, there is an extensive literature review in Hintermann et al. (2016) considering the works dedicated to the phase I and phase II of the market development. Mostly the analysis is applied to the carbon returns rather than prices due to the strong persistence of the data. However, it is possible to find works where the authors find co-integration relationship between variables (see among others Bredin and Muckley (2011), Fezzi and Bunn (2009) and Creti et al. (2012)). For instance, Bredin and Muckley (2011) examine the equilibrium relationship between carbon futures prices and fundamentals, such as energy spreads for electricity production, the Euro Stoxx 50 together, the Eurostat index of industrial production, oil price and a temperature index.

It is important to note that these two types of analysis differ substantially, although often they are treated as substitutes. Thus, analyzing the data in levels one assesses how one variable affect other variables in the system and this influence may be found in the short or long run depending on the persistence of the data. The analysis of returns reveals how the changes in one variable affect the changes of other variables. Thus, it does not contain any information about the long run relationship between variables in levels.

Already at early stage of research on the topic, some authors stress that the relationship between carbon prices with other variables may not be stable or linear. Thus, Alberola at al. (2008) test for structural breaks in the relationship between carbon returns and fundamentals. Chevallier (2011) applies Markov switching VAR to count for possible non-linearities. Creti et al. (2012) analyses the stability of determinants of the CO_2 allowances prices in the Phase I and Phase II.

More late works on EU ETS are characterized by application of more advanced technics, modeling various dependence structures (see Chevallier et al. (2019)) subtracting common information (factor) from various variables (as in Jiménez-Rodríguez (2019)), aimed to capture time-varying nature of the relationship between variables (see Hammoudeh et al. (2014)), or to quantify spillovers running from of variable to another at different moments in the sample (Wang and Guo (2018), Ji et al. (2018)). Hammoudeh et al. (2014) apply a Bayesian VAR to analyze the dynamics of the prices of CO2 emissions in response to changes in the prices of oil, coal, natural gas and electricity. The analysis is produced for the data in levels at daily and monthly frequency. The interaction between variables are quantified on the basis of analysis of impulse responses identified with the recursive scheme ordering CO2 prices as first variable followed by oil, gas, coal and electricity prices. The authors find a positive impact of oil price shock in the short run and negative in the long run. The influence of gas shock is negative. The effect of the electricity price shock is negative. The coal shock does not have significant influence on carbon prices if electricity prices are included into analysis.

Chevallier et al. (2019) apply conditional vine copula approach to model the dependence structure between returns on EU carbon allowances and major energy price returns (coal, gas, oil, electricity). The authors find that “there is a reliable and positive link between coal and gas prices, and between coal and oil prices, with or without the presence of electricity prices, while a weak and positive link is detected between Brent and gas prices. Carbon prices co-move only weakly with energy prices, and their link to oil and gas prices is negative”.

Jiménez-Rodríguez (2019) tests for the causality between the common factor computed from the main European stock market indices and EUA prices and study the evolution of the causal relationship between variables in three different phases of market development. She finds that, indeed, the causality runs from the stock market to EU ETS.

Wan and Guo (2018), and Ji et al (2018) apply mowing window VAR to returns and volatilities of carbon and energy prices and other variables to quantify spillover between variables in the system, computing Diebold and Yilmaz indices based on generalized forecast error variance decomposition. Both works highlight the important role of Brant oil returns in affecting CO_2 allowances returns. Ji et al (2018) find a feedback from the carbon market to other energy markets, and the electricity returns are shown to be the biggest information receiver in the system. Wang and Guo (2018) report a prominent spillover effect of natural gas to carbon market.

In terms of the technics applied, our paper share some ideas with Wan and Guo (2018), and Ji et al (2018) since our aim is to quantify spillover effects of variables in the system. The main differences:

1. We are interested in assessing the impact of the variables to CO2 allowances prices and to the share of fossil fuels (SFF) in electricity production, which is a variable of

primer importance in the analysis, while in before mentioned studies SFF was not included in the analysis.

2. We compute the spillover indices in frequency domain that allows us to decompose them into short, medium and long-run components, that is very important since this decomposition allows identifying the market and fundamental part of the effect of structural shocks.

3. We identify the model. It allows us to assess the signs of impulse responses of variables to the shocks. Instead, under the generalized method the response of the i-th variable to the j-th shock has the same sign as the response of the j-th variable to the i-th shock and the magnitude of these responses differs due to the differences in size of the i-th and j-th errors variance. Additionally, we propose to use frequency band decomposition is identification of structural shocks, separating the influence of fundamental and speculative effects of each shock.

4. We produce the analysis with the data in log-levels. It allows us to evaluate the long-run spillovers between variables.

5. We develop a small theoretical model for EU ETS market, which does good job in explaining CO_2 permits prices movements.

3. Theoretical Model

In this section, we build a small model for the CO_2 permits market prices. The emission permits are issued by the European Commission and distributed through a single EU registry. For the current trading period 2013-2020, which is Phase 3, 57% of the total amount of allowances are auctioned, while the remaining allowances are available for free allocation. At the beginning of the current trading period manufacturing industry received 80% of its allowances for free. This proportion decreases gradually each year to 30% in 2020. Power generators since 2013 in principle do not receive any free allowances; however, some of them are still available in several member states.[2] As it is common in economic modeling we assume that the price of permits is defined by its supply and demand.

The price of CO_2 permits is

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

where P_{CO_2} is the CO_2 price of a 1000t of CO_2; D_{CO_2} is the demand for CO_2 permits and $\bar{Q}$ is the global supply, or quantity of permits available on the market in a year, which is defined as total permits issued in a particular year minus the number of permits distributed for free.[3] That is why the quantity $\bar{Q}$ is constant in a year. The demand, D_{CO_2}, reflects the total emission intensity of the economy.

Reflecting the distinction between final energy consumption and transformation embodied in the ETS scheme, we distinguish between two main sectors that demand CO_2 permits, electricity generation, and industrial processes:

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

Electricity plays an important role in our model. Although electricity consumption does not generate $CO_{2,}$ emissions, electricity production does influence CO_2, emissions.[4] Its generation may be more or less $CO_{2,}$ emissions intense depending on the share of fossil

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[2] The article available online at: https://ec.europa.eu/clima/policies/ets/allowances_en

[3] For the purposes of simplification this theoretical model does not take into account a possibility of using permits issued in year t in subsequent years, which is possible since phase 2 (2008), neither it takes into account a possibility of borrowing allowances from a future allocation for one year to meet the obligations for the current year.

[4] Firms that consume electricity do not buy $CO_{2,}$ permits and thus, electricity demand does not influence $CO_{2,}$ permits demand directly.

fuel energy sources used for power generation, and the emission cost in electricity generation is transferred to the price and paid by the electricity consumers.

Natural gas and coal are the main fossil fuels used for electricity generation in the EU, which are associated with CO_2 emissions. [5] So, total CO_2 allowances demand 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, respectively, and D_{gas}^{ELE} and D_{coal}^{ELE} stand for the total demand of these fossil fuels for power generation. By multiplying equation (3) by total demand of fossil fuels for electricity generation, D_{FF}^{ELE}, and dividing it by electricity demand, D_{ELE}, we get:[6]

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

where s_{FF} represents the share of fossil fuels used for power generation, α_{FF}^{ELE} represents a weighted average CO_2 emission intensity of fossil fuels used for electricity production.

Total CO_2 emissions generated by industrial production, excluding electricity, can be represented as follows[7]:

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

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[5] Although some of 28 Member States still use oil products for electricity generation, their total contribution covers up to 1.6% in year 2017, and is not included here as insignificant.

[6] Here, 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.

[7] Consumption of renewable energy for industrial processes is not included in our model. In 2017, this consumption has reached 0.5% (excluding solid biofuels) and is considered minimal. The remaining 99.5% of industrial energy consumption is composed by coal, natural gas, oil products and electricity. The last is especially relevant as its participation has increased from 28% to 34% in last 20 years.

By adding equations (4) and (5) we get that the total demand for CO_2 permits depends on emission intensities of fossil fuels, their demand, electricity energy demand, and the share of fossil fuels in electricity production:

$$D_{CO_2} = \alpha_{gas} * D_{gas}^{IND} + \alpha_{coal} * D_{coal}^{IND} + \alpha_{oil} * D_{oil}^{IND} + s_{FF} * \alpha_{FF}^{ELE} * D_{ELE} \quad (6)$$

Resuming, our model takes the perspective of final energy consumption. We assign positive CO_2 emissions to four fuels: oil (including petroleum products), coal, natural gas, and electricity[8]. We assume that emission intensities are fixed for oil, coal, and natural gas, and vary for electricity only through the demand for coal and natural gas for power generation[9].

For any fuel type, our model assumes that its demand, D_i, is determined by the following fundamental factors: the production level of the economy that reflect the need for industrial production or consumption of manufactured goods, Y, the relative price of this fuel with respect to other fuels-substitutes, namely a price of fuel i, P_i, compared to prices of other fuels, P_{-i}, and the price of CO_2 permits:

$$D_i = f_i\left(Y, P_i, P_{-i}, P_{CO_2}\right)$$

So, the demand for CO_2 permits can be rewritten as follows:

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

For the vast majority of specifications, Equation (7) can be transformed to a linear function by log-linear approximation, i.e. the log-demand for CO_2 permits $\ln\left(D_{CO_2}\right)$

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[8] In all further notations: "*oil*" stands for oil and petroleum products, "*coal*" stands for coal, "*gas*" stands for natural gas and "*ELE*" stands for electricity.

[9] As equation (4) shows, CO_2 emission intensity of electricity is a weighted sum of emission intensities of natural gas and coal, where demand for natural gas and coal are used as weights.

can be determined by a sum of variables weighted by a factor specifying their importance in (7).

Without loss of generality, a generic demand for permits price can be represented by a linear function, where the natural logarithm of demand in a given period depends on the logarithm of general output of the economy, share of fossil fuels in power generation, prices of fuels available to the producers and price of $CO_{2\ \text{permits}}$:

$$\ln D_{CO_2} = \zeta_1 \ln Y + \zeta_2 \ln s_{FF} + \zeta_3 \ln P_{oil} + \zeta_4 \ln P_{coal} + \zeta_5 \ln P_{gas} + \zeta_6 \ln P_{elec} + \zeta_7 \ln P^R_{CO_2} \qquad (8)$$

The price of permits in (1) can be expressed as:

$$\ln\left(P_{CO_2}\right) = \ln\left(\bar{Q}\right) + \mu_d \ln\left(D_{CO_2}\right) \qquad (9)$$

where $\ln\left(\bar{Q}\right)$ denotes the natural logarithm of real supply and its effect can be considered as a year mean since it is constant in a year, μ_d is coefficient reflecting the importance of the demand on permits in the price-setting function (1). We substitute (8) to (9) and solve for $\ln P_{CO_2}$. Additionally, to account for other factors influencing the price of permits not included in the model we add an error term ε_{CO_2}. Thus, the final specification for the price of CO_2 permits is the following:

$$\begin{aligned} \ln P_{CO_2} &= \gamma_0 \ln\left(\bar{Q}\right) + \gamma_1 \ln Y + \gamma_2 \ln s_{FF} + \gamma_3 \ln P_{oil} + \gamma_4 \ln P_{coal} + \gamma_5 \ln P_{gas} + \\ &+ \gamma_6 \ln P_{elec} + \varepsilon_{CO_2} \end{aligned} \qquad (10)$$

Here an additional complexity arises. The long-run price of CO_2 emissions is determined by the real factors, such as real demand for permits from the industrial sector to cover emissions in a given time period; and by the global supply, or by the number of permits issued a specific year. In its turn, the demand for permits, according to (8), depends, among others, on changes in energy prices determined by fundamental factors. However, given strong financialization of the market, the CO_2 emission permits as much as other energy futures, became a financial instrument, whose short-term price dynamics are sometimes influenced by events that have little to do with economic determinants of their prices (for example, some transient phenomena like sporadic events and psychological factors). To reflect this situation, we assume that the long-run determinants of the CO_2 permits and other fuels prices are attributed to economic factors (or changes in the fundamental part of the price) only, while the short and medium-run – mostly, to the changes in market microstructure. Formally, it means that the term ε_{CO_2} in (10) consists of two unobserved components: $\varepsilon_{CO_2} = \varepsilon_{CO_2}^F + \varepsilon_{CO_2}^M$, where $\varepsilon_{CO_2}^F$ denotes unexpected changes in fundamentals, not accounted by the model, and $\varepsilon_{CO_2}^M$ unexpected CO_2 market specific shocks.

Although the time index is omitted in Equation (10), we expect time variation in coefficients γ_k, $k = 0,...,6$, given that they depend on a-priory time-varying parameters, such as the share of gas and coal demand in electricity production in (4). Even CO_2 emissions intensity of fuel *i*, α_i, $i = oil, gas, coal$ may change with the level of technology. Thus, the empirical model should account for time-variation in model parameters.

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 $N \times N$ matrix $\Lambda(L)$ in (12) are infinite polynomials whose coefficients are the impulse responses (IRF) of the variables to the structural shocks. The matrix A is the structural matrix relating reduced form and structural shocks $\varepsilon_t = A\xi_t$, therefore $\Omega = AA'$. Given that A has N^2 distinct elements and Ω is symmetric and has just $N(N+1)/2$, additional identification assumptions should be imposed to identify A.[10]

4.2 Measures of Connectedness in the Frequency Domains.

To analyze the contributions of shocks to the variances of variables at different frequency ranges (short-run, medium-run and long-run) we compute the variance-frequency decomposition and thereafter calculate some frequency domain connectedness measures based on this decomposition (for details see Barunik and Krehlnik (2018, 2017)).

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

[10] Specifically, we require $N(N+1)/2$ restrictions. In addition, one should also impose an auxiliary assumption on the sign of elements of the main diagonal of A.

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

where $i = \sqrt{-1}$ is 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 $F\left(e^{i\omega}\right)$, $\omega = \frac{2\pi j}{T}$, $j = 1,...,\frac{T}{2}$. It represents the portion of variance of the *j-th* variable at a frequency ω due to the *k-th* shock.

However, in economic and finance applications, the share of a shock in the variance of a variable in a single frequency does not provide necessary information for the analysis. Usually, main interest is concentrated around, short-, medium- or long-run contribution of a shock to a variable variance. Upper and lower limits of each band depend on the data frequency. Formally, for a frequency band $d = (a,b) : a,b \in (-\pi, \pi), a < b$, the variance-frequency decomposition on frequency band d is defined as

$$f_{j,k}^{d} = \int_{a}^{b} f_{j,k}(\omega) d\omega \tag{13}$$

The definite integrals in the previous expression can be approximated by the summation over Fourier frequencies inside band. These measures represent the portion of variance of the *j-th* variable on frequency band d due to the *k-th* shock. Based on this notion, we will define a *within* frequency connectedness measures. They are suitable to compare importance of a shock in the variance of a variable at different frequency bands or importance of different shocks in the variance of a variable at a given frequency band.

The pairwise *within* frequency connectedness measures can also be summed for all $k \neq j$ to get directional measures of *within* frequency connectedness. The directional *within* frequency connectedness from others on a frequency band is defined as:

$$f_{j\leftarrow\bullet}^{d} = \sum_{k=1,k\neq j}^{N} f_{j,k}^{d} \quad (14)$$

Note, however, that the summation of *within* measures over all bands considered will not produce total contribution of a shock to the variable's variance given that these quantities do not reflect the importance of each frequency in the total variance of this variable. To overcome this shortcoming, we pre-multiply the causation spectrum by the weighting function, reflecting the power of the *j-th* variable at a frequency ω:

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

As a next step, we compute the variance-frequency decomposition on a band d, taking into account the importance of each frequency in the total variance.

$$\Theta_{j,k}^{d} = \frac{1}{2\pi}\int_{a}^{b}\Gamma_j(\omega) f_{j,k}(\omega) d\omega \quad (15)$$

The frequency connectedness index also can be extended to directional measures of frequency connectedness. The directional frequency connectedness from others on a frequency band is defined as:

$$\Theta_{j\leftarrow\bullet}^{d} = \sum_{k=1,k\neq j}^{N} \Theta_{j,k}^{d}. \quad (16)$$

If the band d corresponds to whole range of frequencies, i.e. $d = D = (-\pi, \pi)$, we get the total contribution of *k-th* shock to the variance of *j-th* variable, $\Theta_{j,k}^{D}$. Unlike for *within* measures, for this measures of connectedness, choosing a partition of the interval D into s bands such that $d_s, \forall s$ satisfies the following conditions: $\bigcap d_s = \varnothing$ and $\bigcup d_s = D$, then

$$\Theta^D_{j,k} = \sum_s \Theta^{d_s}_{j,k} \,. \qquad (17)$$

As Barunik and Krehlnik (2018) shows the total contribution of *k-th* shock to the variance of *j-th* variable, $\Theta^D_{j,k}$, is equivalent to the time domain Diebold and Yilmaz (2015) connectedness measures.[11]

5. Empirical Model

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

5.1 Data Description

For the real economy determinants, we choose the following approximations for the model's variables. For the prices of fuels, we choose 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}[12]. Respecting the timeframes, for the process of carbon permits we take first-month future contracts for P_{CO2}[13]. We use futures contract prices for energy products because future prices are less affected by short-run noise than spot, and more actively traded (Sadorsky, 2001). Besides, the majority of studies on connectedness in different markets use futures prices. For economic output variable, we use economic activity index STOXX for the EU, which data is also available on a weekly basis[14]. Inspired by Kilian (2009), we repeat the analysis with the Baltic Dry

[11] Diebold and Yilmaz (2015) summarize the results of Diebold and Yilmaz (2009, 2012, 2014).

[12] Weekly data was collected through Thompson Reuters Eikon platform, contracts *LCOc1*, *TRNLTTFMc1*, *ATWMc1*, *TRDEBMc1*.

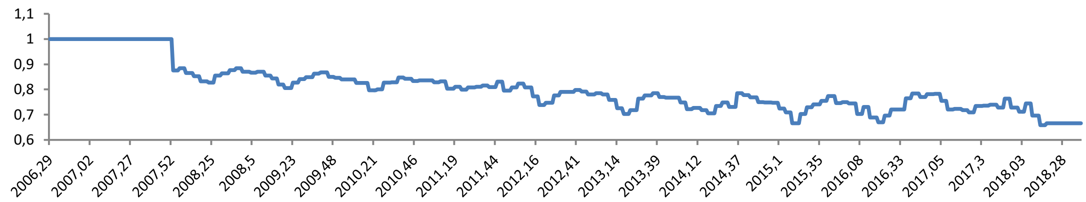
[13] Weekly data was collected through Thompson Reuters Eikon platform, contract *CFI2Zc1*.

[14] Weekly data was collected through Thompson Reuters Eikon platform, *SPE350*.

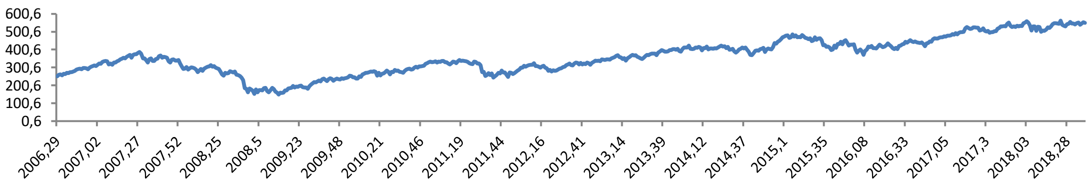
Index as a measure of economic activity to check robustness of the results to the definition of the variable.[15] Renewable electricity share data is collected at the EU level on a monthly basis and is taken from energy published by Eurostat[16]. The data sample runs from 1st week (7-13 of January) of 2008 to 39th week (24-30 of September) of 2018. The starting point is restricted by the availability of data on renewable electricity share. All series are depicted in Figure 1.

Figure 1. Data

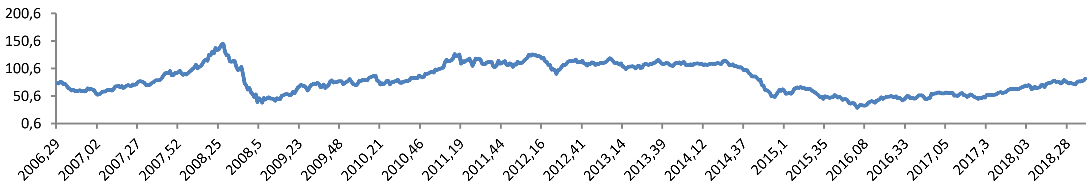
Share of Fossil fuels



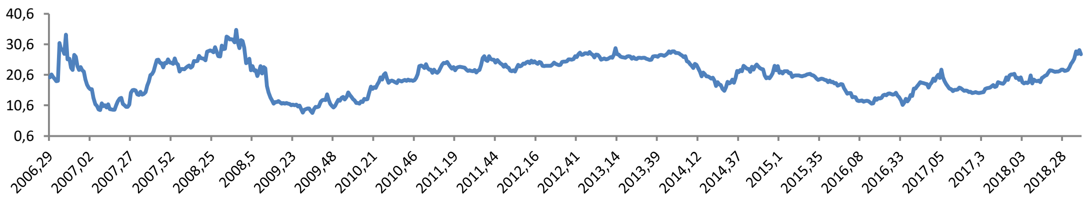
Economic indicator



Oil prices



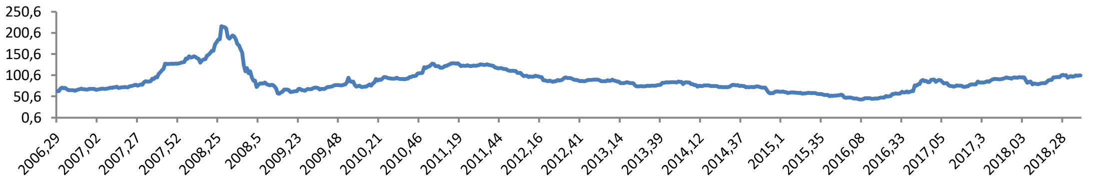
Gas prices



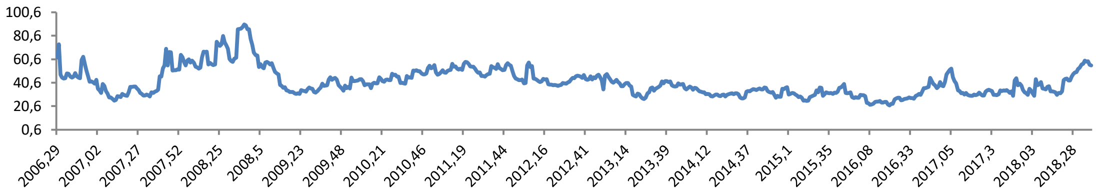
Coal prices

[15] Weekly data was collected through Thompson Reuters Eikon platform, BADI.

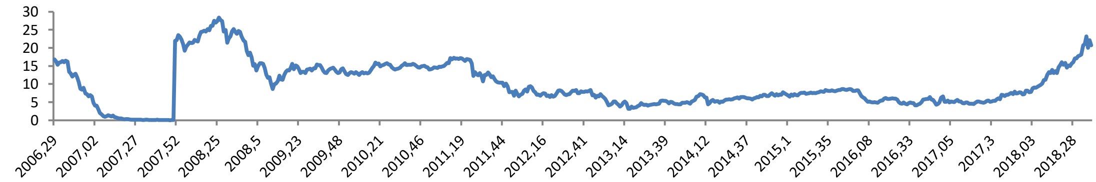
[16] Monthly data on EU level is available in "Eurostat nrg_150m" data base published by Eurostat at http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_105m



Electricity prices



CO_2 permits prices



We collect variables in a vector X_t, all expressed in natural logarithms:

$$X_t = [\ln sFF_t, \ln Econ_t, \ln P_{oil,t}, \ln P_{gas,t}, \ln P_{coal,t}, \ln P_{ele,t}, \ln P_{CO_2,t}] \tag{18}$$

We have chosen the log-level specification by several reasons. First, this specification allows for a wider range of functional forms for the theoretical model in Section 3, allowing us not to specify closed functional forms. Note that non-linear functions can be log-linearized to achieve linear approximations. Second, the log-log model has a constant elasticity interpretation of the parameters. The third reason is technical. Financial data is known to be skewed and the logarithmic transformation alleviates this problem. Finally, note that given that we estimate the model over a rolling window, we are implicitly assuming that log-variables are stationary “locally” across subsamples. Although all present considerably persistence, differencing would remove the (co-) variances at low-frequencies completely, changing the way the variables interact in the model and biasing the responses of the variables to shocks (Gospodinov et al. 2011; Lovcha and Perez-Laborda 2019). As a result, their long-run relationships, key for the purposes of this study, would get lost. Note, however, that energy prices and other energy variables are very often assumed stationary and included in log-level forms in the VAR (see, e.g., Kilian, 2009, 2010, Hammoudeh et al. 2014). The advantage of the log-level specification here is that the VAR estimates remain consistent even if the prices contain unit roots, with asymptotically valid inference on impulse responses. On the contrary, falsely imposing unit-roots generates inconsistent estimates.

Some of the variables require transformations to match the theoretical model. According to equation (11), CO_2 prices are affected by demand factors but also by the supply of permits, which is constant in a year. Unfortunately, the short data span available does not allow us to quantify the importance of supply shocks in CO_2 prices. However, its effect is significant and cannot be neglected even in a rolling window estimation of only three years. Consequently, we focus on the quantification of demand-side effects only by transforming the dependent variable to account for yearly supply changes, i.e., by subtracting the yearly mean to each observation. In this way, we account for yearly specific effects that are a consequence of changes in the supply of permits together with other yearly specific factors.[17]

Figure 2. CO_2 price series, yearly mean and the mean adjusted series.

[17] Another way to treat year effect is to include year dummies to the estimation. However, in rolling window estimation, the estimated dummy coefficients for not full years, entering the sample, would change depending on the number of observation included. Subsequently, they would be strongly influenced by sample-specific effect, introducing noise to the year specific effect we aim to subtract.

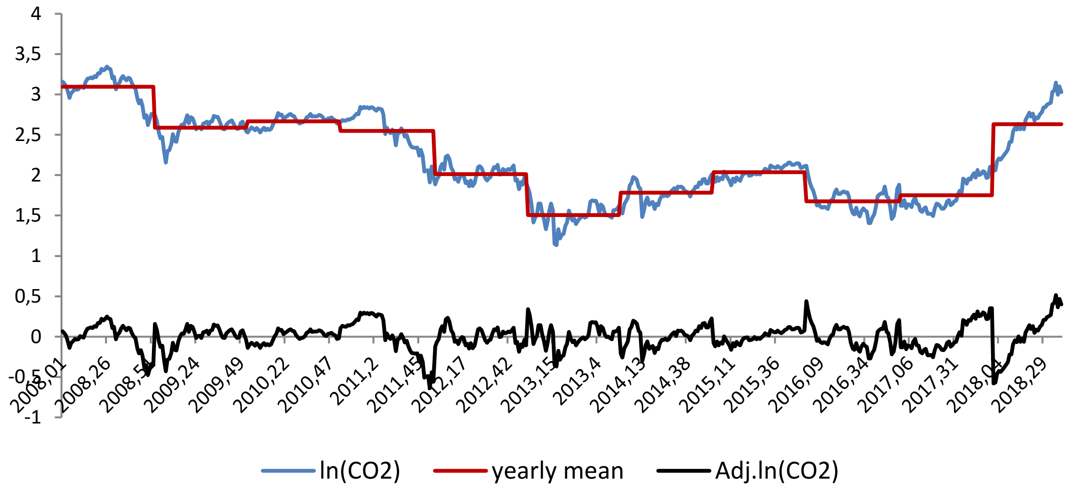


Figure 2 depicts the natural logarithm of the CO_2 price together with its yearly mean and the mean adjusted price series. The importance of yearly specific effects can be approximated by the percentage of the log-variance of the permit price accounted by changes in yearly-specific factors. Over the complete sample, yearly changes in the mean account for around 90% of the CO_2 price variance. Given that the permit market is highly controlled, we believe that this high percentage is mostly due to changes in the supply of permits. Note, however, that permits demand (either fundamental or speculative) is responsible for 100% of the fluctuations inside the year and for the fluctuations with frequencies lower than one year.

We also transform the share of fossil fuels in electricity production (SFF). Weather conditions for wind, hydro and solar power generation present seasonality, and therefore the SFF is seasonal. For instance, if a day is not windy, wind power installations cannot produce electricity, and producers must increase the portion of fossil fuels to satisfy demand. Short-frequency weather shocks have little or no influence on monthly SSF due to their random nature. However, the SFF still presents seasonality with a longer period; for example, there are less sunny days in winter. Being caused by cyclical natural phenomena, the seasonality is reasonably stable and well approximated by constant trigonometric seasonal components at corresponding frequencies around 12 periods (one year) moving average mean. Even though we allow for some randomness in seasonal effect and seasonally adjust the series with Tramo-Seats. Subtracting higher frequency seasonality, we get rid of most of the weather influence.

Once the series is seasonally adjusted, we interpolate the observations inside a month. For the interpolation, the observations inside month are computed as $s_t^{n_t} = S_t$ for the last week in a month and $s_t^{i-1} = s_t^i - A_i \left(S_t - S_{t-1} \right) / n_t$, $i = n_{t-1}, n_{t-2}, ..., 1$ for previous weeks, where S_t is observed monthly variable with the subscript t standing for the number of month, i is a week inside each month, such that $i = 1, ..., n_t$, n_t is a number of weeks in a month t, takes values four or five, A_i is a week specific coefficient. If this coefficient is equal to one, the interpolation is made by linear projection, where the last week in a month observation coincides with the observed monthly observation. However, allowing A_i to be i.i.d. $N(0,1)$, we add randomness to the linear interpolation. We choose the second interpolation method as a benchmark.

5.2 Identification Restrictions

Structural shocks in the SVAR are conceptually defined as shifts in the corresponding model variables that are not anticipated by the model. As noted in Section 2, we require additional restrictions to identify the structural shocks from the reduced-form VAR estimation. In the spirit of Kilian (2009, 2010), we identify the model placing zero contemporaneous restrictions on the variables. More specifically, we assume that variables situated above $Y_{i,t}$ are not contemporaneously affected by variables situated below; that is, the structural matrix A in (12) is lower-triangular. For this reason, the variables in the vector (18) have been ordered according to their nature, in order to place fewer contemporaneous restrictions on more reactive (agile) variables.

The first variable in (18) is the SFF. Since this variable was only available at a monthly frequency, it seems reasonable to assume that unexpected weekly changes in prices or activity cannot influence it contemporaneously. In addition, the installed power capacity from renewables is fixed at short run since it requires time to be built. 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 CO_2 prices, 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. No contemporaneous restrictions have been placed on the CO_2 market because this variable can be contemporaneously affected by all other variables according to Equation (10) in the theoretical model. Consequently, the CO_2 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 in Equation (10) augmented with lagged variables. However, in Equation (10), the CO_2 market-specific shock is split up in two components, i.e. $\varepsilon_{CO_2} = \varepsilon_{CO_2}^F + \varepsilon_{CO_2}^M$. The first component, $\varepsilon_{CO_2}^F$, collects the reaction of CO_2 prices to changes in omitted policy and fundamental variables. The second, $\varepsilon_{CO_2}^M$, 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 decomposition variance to isolate their effects. In particular, we assume that unexpected changes in the speculative demand for permits have relatively short-living effects only, of at most half-a-year, although the majority vanishes faster, in one month. Therefore, the long-run effects of the CO_2

market-specific shock represent changes in omitted policy or fundamental variables only. The same is applied to shocks to other markets. Thus, the oil, gas, coal, and electricity-market specific shocks influence other variables in the short-middle or long run, reflecting either short-living changes in speculative market-specific demand or more long-living shift in market fundamentals. This type of identification allows us to assess the importance of fundamental market-specific factors in CO_2 price setting and isolate them from financial, however not less important, market phenomena.

5.3 Estimation Strategy

It is very unlikely that SVAR parameters have remained constant over time. We follow the standard practice of estimating the VAR over a rolling window to account for possible changes in the parameters over time, by adding and taking one observation each time. The length of the rolling window corresponds to T=156 points (approximately 3 years).

Concerning the model specification, we allow for four lags in the autoregressive part according to Akaike and Schwarz criteria.

Frequency connectedness is evaluated at three frequency ranges: short-run with period from one to four weeks, corresponding to one month approximately, medium-range with period from five to 26 weeks, or from one month to half-an-year; and long-run from 27 weeks to 156 weeks. The lower bound for the long-run frequency band is set with the idea that all speculative market-specific noises are absorbed and “digested” by the market at a shorter than 27 weeks horizon and the rest is the influence of the fundamental factors. The upper bound is the number of observations in the window.

6. Empirical Results

We present the empirical results giving priority to two issues of policy relevance.[18] First, we assess the determinants of CO_2 emission prices in order to understand how sensitive they are to the market forces, and how the nexus between CO_2 price and the CO_2 demand fundamentals have evolved over time. Specifically, we want to investigate to which extent recent increases in CO_2 prices can be explained by changes in carbon demand fundamentals or, rather, are just the consequence of speculative movements in the CO_2 market. Second, we study how changes in model variables affect share of fossil fuels in electricity, SFF. In this way, we provide an insight into the overall effectiveness of the ETS system. Finally, we zoom in on other useful details of the results, such as natural gas and carbon markets and their role in recent dynamics of CO2 prices.

6.1 The determinants of the carbon emission prices

6.1.1. CO_2 price: aggregated connectedness from other variables

The solid black line in Figure 4.a is the index of total connectedness from other variables to CO_2 prices across rolling subsamples (CO_2FROM), computed applying (17).

Figure 4. Connectedness FROM others to CO_2 prices

Figure 4a. The CO_2 FROM and its decomposition into the short, medium and long-term components

[18] All the results are available upon request.

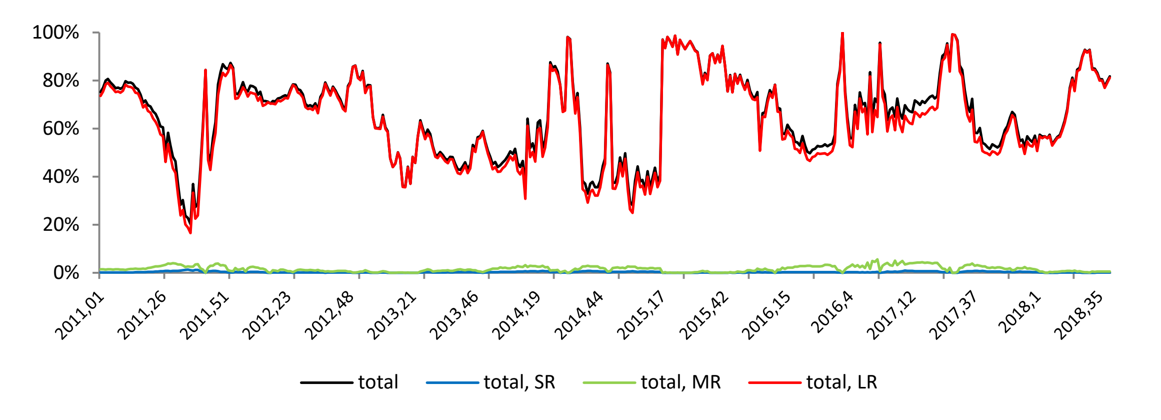
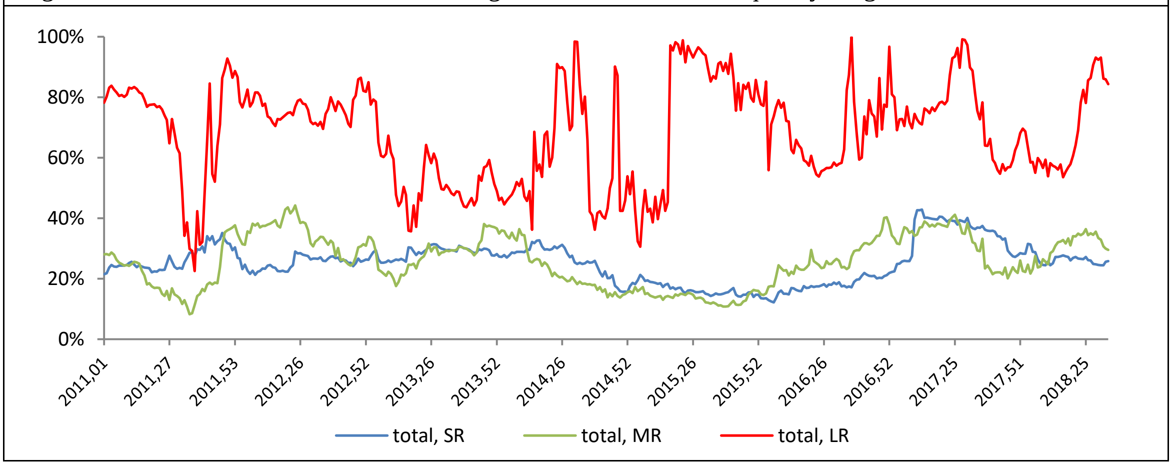


Figure 4b. Connectedness created within high, medium and low-frequency ranges



The CO_2FROM index quantifies the extent to which uncertainty in CO_2 prices is explained by shocks to the other variables, or, in other words, by the unexpected fluctuations of variables included to the model. These other variables are the main drivers of the demand for CO_2 allowances according to Equation (11) and, thereby, CO_2FROM index reflects the explicative power of the model.

On average, shocks to other variables explain 65% of the permit price variance, which is a high percentage for weekly fluctuations. Yet, we found substantial variation across subsamples. As the figure shows, the index presents several spikes, alternating periods of high connectedness with values over 90%, like in second quarter 2017, with other periods where connectedness is relatively low, like in the first quarter of 2015, where the index was lower than 30%. Note, however, that the model explains a considerable portion of the CO_2 price variance after 2016, yet with a moderate drop during the second half of 2017. The average value of the index since mid-2018 is 85%, implying that an increasing portion of the recent CO_2 price fluctuations is explained by the model.

Figure 4a also decomposes the CO_2FROM index into its short, medium and long-term components, as in (16), using the frequency-domain methodology in Barunik and Krehlik (2018). These components quantify, respectively, the percentage that transmission at high, medium and low-frequency ranges has over the total CO_2 price fluctuations. As Figure 4a shows, the long-term component of the CO_2FROM index accounts for most of the transmitted variance, indicating that CO_2 prices movements are mostly due to changes in the explicative variables produced by the fundamental factors having the long-run effects, dissipating slowly on the long-run. The portion of the medium-run component in total fluctuations is very small, and that of the short-term component is virtually imperceptible. It means that market specific speculative shocks or other transitory events affecting other variables contribute little to total CO_2 prices fluctuations. Yet, the previous decomposition does not necessarily imply that these phenomena are not important in the permit price determination at higher ranges. Speculative shocks could still be an important factor for the CO_2 price at high or medium frequencies, but this may not be reflected in Figure 4a because the CO_2 price is very persistent and fluctuations at high ranges have little weight in its total variance. They are small relative to low-frequency fluctuations, but for certain agents, such as short-term investors, they are enormously important as their short trading horizon is only affected by high-frequency movements. To shed light into this issue, Figure 4b presents the connectedness that is created specifically *within* the frequency ranges. The within indices quantify the importance that transmission from other shocks has in CO_2 price fluctuations at the specific frequency range and it is computed as in (14).

As Figure 4b shows, other variables explain a large share of the fluctuations of the CO_2 price at low frequencies. In fact, as the shape of the total CO_2FROM index across subsamples mirrors the transmission within the low-frequency range, the weight of low frequency range in total variance is very high. However, the model still explains an average of 25% of the emission price fluctuations at high and middle frequencies. The shares are considerably smaller than the ones at low frequencies, especially since mid-2018, where other shocks explain around a 85% of the low-frequency CO_2 price fluctuations. Yet, although small, the percentage is not negligible, indicating that even in the short and medium run the CO_2 price is affected by the transitory phenomena that occurs in other markets.

Overall, our results indicate that the model in Section 3 does a good job in explaining carbon price fluctuations, as the effect of own shock is fairly limited and the variation in other variables expalins high portion of variance at different frequency ranges, especially after mid-2018. We consider these issues further in the next section, where we discuss the importance of each variable in carbon price fluctuations, including the CO_2 market-specific shocks.

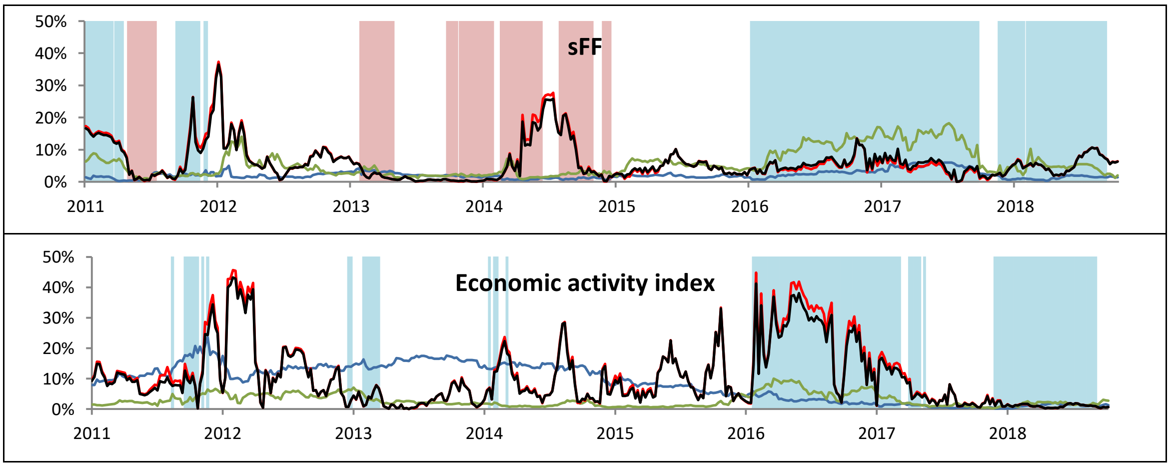
6.1.2. CO_2 price: Connectedness from each model variable

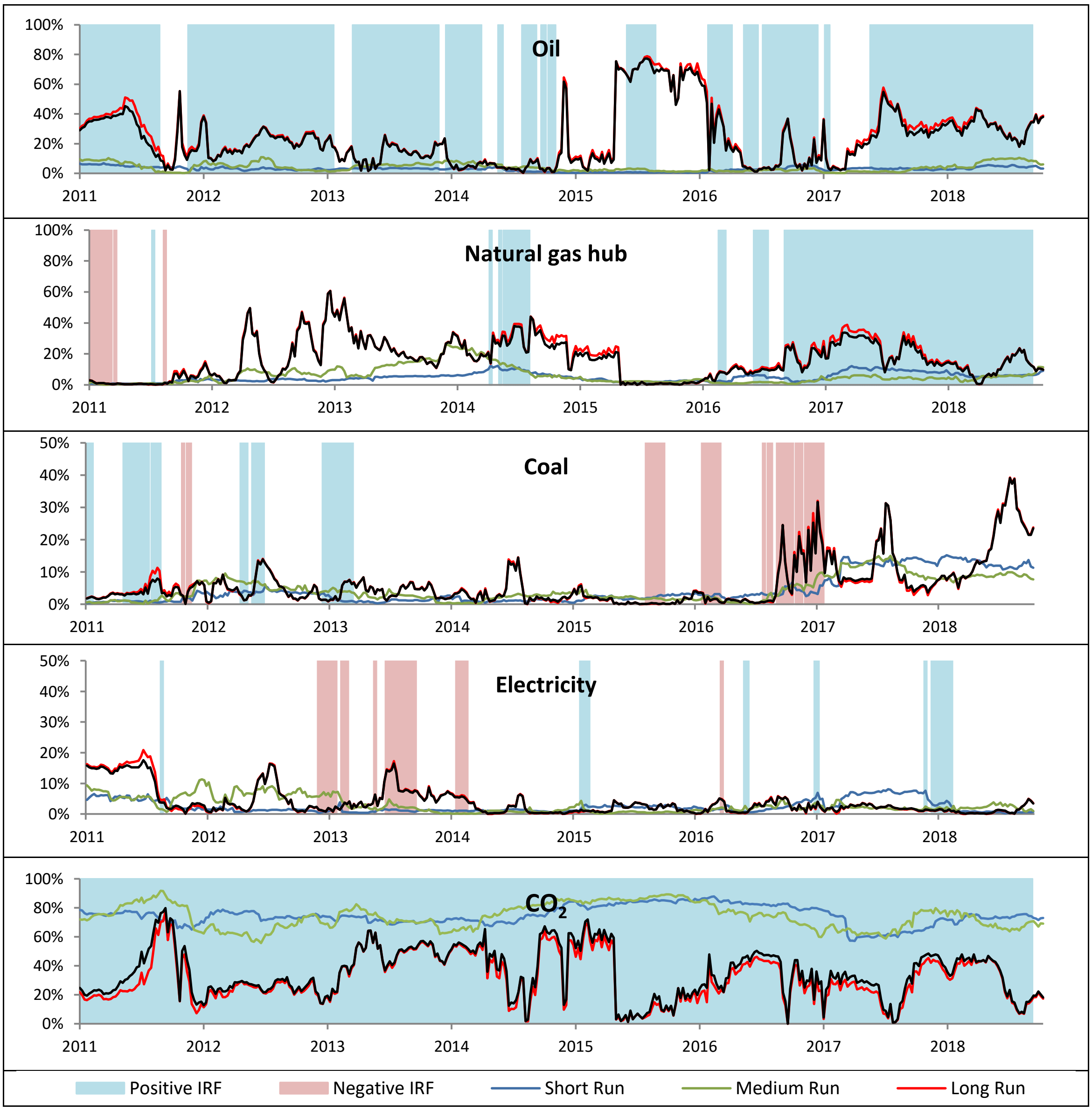
To investigate the determinants of the transmission mechanism further, Figure 5 present time-varying pairwise indices of connectedness from each model variable to the CO_2 price. Pairwise indices quantify the percentage that each variable explains in the total CO_2 price fluctuations and add up to the total CO_2FROM index in Figure 4a when aggregated over all variables, except CO_2, i.e. if we sum all, except the one on the last graph, black lines in Figure 5 we get the black line in Figure 4a.

We also evaluate the (weighted) connectedness on the frequency band, as in (15). However, we do not report the decomposition of the pairwise indices into its short-, medium-, and long term components to save space since the long-term component accounts for virtually all the corresponding index, as in Figure 4a. Instead, we include in Figure 5 the connectedness created within the three frequency bands in order to quantify the importance of the variables on the fluctuations of the permit price at the specific range. Note that the pairwise within connectedness over frequency band add up (excluding CO_2) to the total within connectedness over corresponding band, specifically, all red (green/ blue) lines, excluding the one in the last graph, in Figure 5 add up to the red (green/ blue) lines in Figure 4b.

Besides, in this disaggregated analysis, we also discuss the signs of the response of the CO_2 price to structural shocks to provide additional insights into how the permit market system was functioning over time. We have highlighted with blue color in Figure 5 the subsamples where a (positive) structural shock increases the price for at least the first four following weeks. Red areas are subsamples where the positive shocks in fundamental variable induce a decrease in CO_2 prices for the first four periods.

Figure 5. Connectedness to CO2 prices: total, short, medium and long-term frequency components





As the first panel of Figure 5 shows, there are two clearly identifiable periods for the sign of the response of the CO_2 price to a shock in SFF. Against economic intuition, the sign is predominantly negative before 2016, implying that an unexpected increase in SFF decreases the CO_2 price. From 2016, however, the sign turns positive, as the theory predicts, as higher SFF implies a higher demand for fossil fuels, thus a higher demand for permits. The overall importance of specific shocks to SSF for emission prices is moderate. We find a spike in connectedness around 2014 that could be a consequence of oversupply of permits. At that time economic activity was still below 2011 levels, and some of the permits were still allocated to electricity plants for free (recall that the CO_2 price has a reversed sign in this period). However, the index barely reaches 10% in recent years, where the response of carbon prices is as expected. This can be partially explained by the fact that SFF is exogenously determined by the power generation capacity mix, which has not changed dramatically in the last years. While electricity producers are slowly switching away from fossil fuels, they still use them more when RES production decreases o electricity demand goes up. As frequency band decomposition suggests the SFF shock has mostly long lasting effect, when the connectedness between variables is relatively high, as at the end of 2011 – beginning 2012 and middle 2014. Also, there is a period of a relatively high importance of this variable in middle range variance of CO_2 in 2016-2017 coinciding with the expected sign of the CO_2 price response. The short-run component is almost negligible that is consistent with monthly frequency the data is available.

As expected, shocks to economic activity are positively associated with CO2 prices, especially from 2016. Economic expansions imply higher demand for fossil fuels, hence a higher demand for permits. As Figure 5 shows, economic activity is an important determinant of the CO_2 price fluctuations. On average, around 10% of the total CO_2 fluctuations are explained by activity shocks. However, the contribution has varied substantially across subsamples. Starting from 10% in 2011, connectedness from activity reached 40% of the permit price fluctuations in 2012. In 2013, however, the share was low because economic activity was still well below the 2011 level. From 2013, the index steadily increases and gets back to 40% in 2015. Since 2016, however, the importance of activity markedly declines and transmission from economic activity is currently responsible for only five percent of the total CO_2 price variance. Therefore, our results point towards a progressive decoupling of the carbon market from activity, consistent with some emission-output independencies in EU countries stressed in recent literature (see, e.g., Cohen et al., 2018, Wu et al. 2018).[19] As for the frequency band decomposition, the results suggest that the connectedness running from economic activity is generated mostly in the long-run run (black and red lines almost coincide). However, the within band short run connectedness from economic activity reaches almost 15% in period from middle 2011 to middle 2014 that points out toward significant interconnection between markets at that period, signaling that stock market short living phenomena were reflected into CO_2 price short-run movements.

Although oil and refined petroleum products generate CO2 emissions, their use in EU countries concentrated mostly in the transportation sector, which is not subject to the ETS. However, we still include the price of oil in the model because it reflects two factors simultaneously. First, it has traditionally been a good proxy for the long-term natural gas price, as indexation of the price of gas to oil has been a common practice in Europe since the 1960s. Although the share of oil indexation has decreased, still many long-term gas contracts are indexed to oil prices directly or indirectly. In fact, most studies find evidence of a long-run relationship between the two prices in Europe (see, e.g., Lin and Li, 2015). The second reason is that the oil price reflects a global component of the energy system and economy, as it is the most largely traded commodity in the world. Consistent with both reasons, we find a positive oil price shock to be associated with an increase in the CO_2 price. On average, oil shocks account for around 20% of CO_2 price fluctuations. The importance of oil, however, is larger in the second half of our sample. In particular, it started with a strong connectivity episode in 2015-2016, after the oil price crash generated by the enormous glut. Supporting the

[19] The result is stable if instead of STOXX index we repeat the analysis with the Baltic Dry Index as a measure of economic activity (see Kilian (2009)).

idea that the oil price reflects a global component of the energy system and economy, the information transmitted from this market has mostly long run effect to CO_2 prices and can be considered as fundaments. Short run and middle run within band effects of oil market are very low, not reaching 10% at any period in the sample.

A natural gas shock is associated with an increase in the CO_2 price, as theory predicts. Increases in the price of natural gas give to its closest substitution fuel, coal, a competitive advantage, thus raising coal's demand. As coal emits more CO_2, substitution incentives raise the demand for permits and its price. Our empirical results support these predictions, especially in the last part of the sample. Overall, the variations in natural gas hub prices explained up to 50% of the CO_2 price fluctuations in 2011-2015, and up to 30% since mid-2016. We observe a huge drop in the pairwise index in 2015-2016, consistent with the increasing importance of the oil price during this period, as stressed above. Within frequency band connectedness signals the importance of the gas market in the long-run CO_2 price variations. However, the short, and especially, middle-run connectedness running from the gas market should not be neglected. Thus, it reaches 20% in 2014, making the gas market the main transmitter of variation at this frequency band.

Consistently with the results for natural gas shocks, positive shocks in coal prices are associated with a decrease in CO_2 prices, as the higher the price of coal, the largest incentives to substitute it with natural gas. Coal market-specific shocks did not explain more than 10% of the permit price fluctuations until 2016; however, it explains significantly more after, with strong peaks in connectedness in mid-2017 and mid-2018 probably consequence of the shortages generated by the strong environmental requirements. Importance of coal market in middle and short run CO_2 price fluctuations increases starting from 2017.

As for electricity market-specific shocks, we observe rather undetermined results on the sign of carbon price response. Also, as expected, we observe low overall importance of electricity for emission prices, especially from 2014. Note that high connectedness episodes have virtually disappeared from the start of Phase 3 of the ETS system in 2013, where free allocations for electricity generation were eliminated. CO2 emissions, together with fossil fuels, are inputs for electricity generation, and that is why it is the CO2 price who directly impacts electricity prices and not vice versa. However there are also two indirect channels. First, electricity and CO2 markets are closely related, suggesting expectations synergies, and that is why electricity price has more importance in explaining short-term variance of CO2. Second, before Phase 3, electricity price shocks could influence carbon market through demands of electricity and fossil fuels (as substitutes or complements for industrial products), the channel, which disappeared in 2014, when electricity facilities fully assumed CO2 costs of their generation.

Finally, Figure 5 also provides detailed results on the effect of CO_2 market-specific shocks. As shocks have been normalized to be positive, the CO_2 shock increases the permit prices by assumption. This shock accounts for around 35% of the total carbon price fluctuations across subsamples (the portion not accounted by other shocks in the model), but its share has considerably reduced since mid-2018. According to our interpretation, the long-run effects of the shock reflect the policy channels or fundamental variables that are not included in the model, while the medium and, especially, the short-run effect, come from speculative shocks in CO_2 market.

As Figure 5 shows, the CO_2 shock accounts for a relatively small percentage of the low-frequency price fluctuations, the same percentage than in total. As already noted, this implies that the effect of omitted variables in the model is quite limited and the model works well, especially in later periods. However, the most interesting results arise when we concentrate on short and medium-run fluctuations. Note that unlike the other structural shocks, the CO_2 market shock explains a large share at these ranges, being on average responsible for 80% of the high and medium frequency fluctuations of the permit price. Thus, our results show the importance of speculative shocks in the CO_2 market, but only for the high-frequency swings of the permit price. Actually, notice that the contribution of the fundamental variables at the high-frequency range is generally marginal. Only the coal market-specific shock has a significant effect on the high CO_2 price fluctuations in recent years, although its importance at low frequencies is still substantially larger. Shocks in the electricity market also seem to have been a source of high-frequency uncertainty in recent years but the overall importance of this shock is very small.

Summarizing, we show that shock transmission from the determinants of the fundamental demand for permits explains a significant share of emission prices fluctuations, and its importance has increased in the later period. Still, unaccounted changes in EU policy on ETS markets may have served as an enabler of the considered demand forces in determining carbon prices, as the carbon market shock explain a non-negligible part of the fluctuations.[20] However, it is difficult to disentangle conceptually or quantitatively their effects from other omitted fundamental variables that may also influence the price. Transmitted shocks from demand driving variables are more important for the long-run fluctuations of the permit price, with a period longer than half a year. On the other hand, speculative shocks on the CO_2 market are, with a large difference, the most important factor in explaining its high-frequency movements.

[20] The policy is a broad concept here, and it includes the notions of how the market is designed, organized and operated, how the expectations are formed.

However, transmitted fluctuations at high frequencies represent only a very small percentage of all price movements.

Our results also indicate that the main drivers of uncertainty among demand determinants have been changing over time. Historically, economic activity and natural gas hub prices were important drivers of the CO_2 fluctuations but their role has been decreasing, in favor of other variables, such as oil, and especially coal. Therefore, our results signal that EU countries are succeeding in decoupling production from emissions. Our results also point that, due to necessary policy adjustments, namely limiting the number of permits, we do observe a positive relationship between SFF and CO_2 prices after 2016.

6.2 The determinants of the fossil fuel share in electricity generation

6.2.1. SSF: aggregated connectedness from other variables

Figure 6 presents time-varying measures of connectedness to SSF from the other variables in the model.

In particular, Figure 6a depicts the evolution of the FROM index from all variables (SSFFROM), computed applying (17), together with its decomposition into short, medium, and long-term components, as in (16). As the figure shows, a considerable portion of the SSF uncertainty is explained by the other variables in the model. On average, transmission from other variables accounts for 45% of the SSF fluctuations, however, there is also substantial variation and in some periods, such as mid-2017, the index is substantially larger, sometimes over 90%.

Figure 6. Connectedness FROM others to SSF

Figure 6a. SSFFROM and its decomposition into short, medium and long-term components

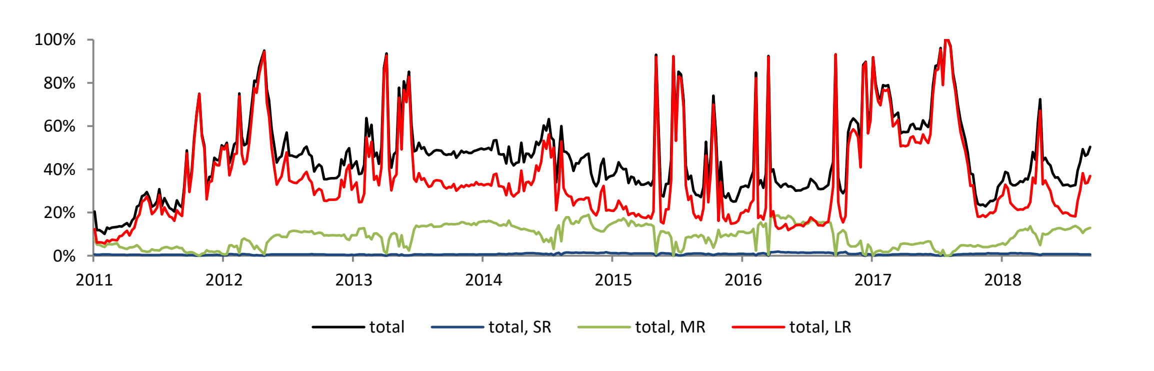
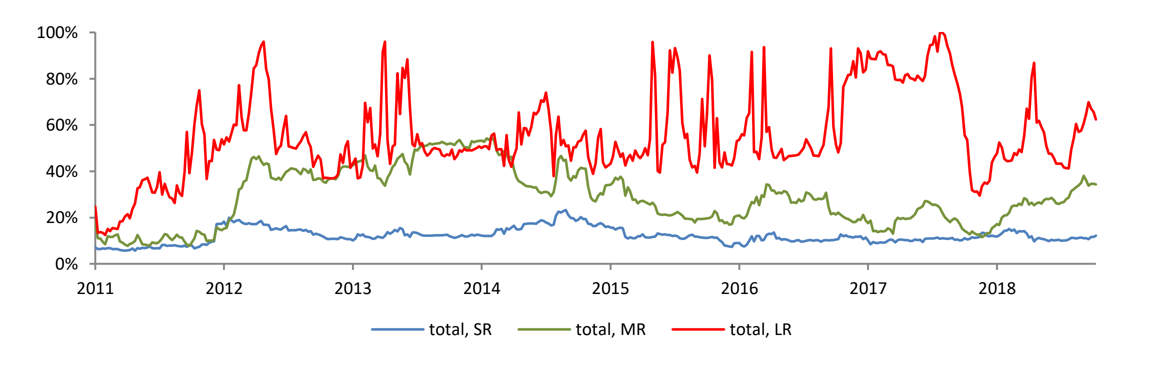


Figure 6b. Connectedness created within high, medium and low-frequency ranges



The long-term component of the SSFFROM index is considerably more important, thus transmission from other variables to SFF mostly generate low-frequency fluctuations on the SSF. The medium-term component is also important, albeit considerably less than the long-term. Specifically, transmission at low frequencies accounts, on average, 35% of all SSF fluctuations, while the medium and short-term, 9% and 1%, respectively.

Note, however, that the monthly frequency at which SSF was available, together with the seasonal adjustment to get rid of the influence of short-term weather conditions, has removed a large portion of the high-frequency variance, thus penalizing the importance of high-frequency SSF fluctuations on the total. To account for this fact, Figure 6b depicts the connectedness created specifically *within* the different bands. As the figure shows, our previous results were robust. Shocks from other variables are considerably more important for low- and, to a lower extent, medium-frequency fluctuations of the

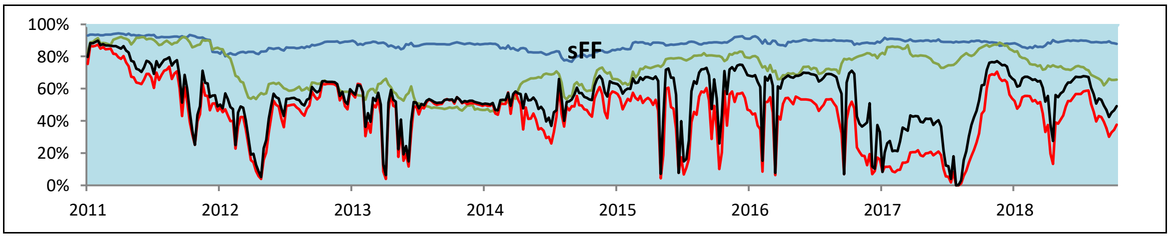
SSF. The weight of other variables on the high-frequency fluctuations of SSF is still small, roughly 10% on average.

The particular importance of each shock for SFF fluctuations is presented and discussed in the following sections.

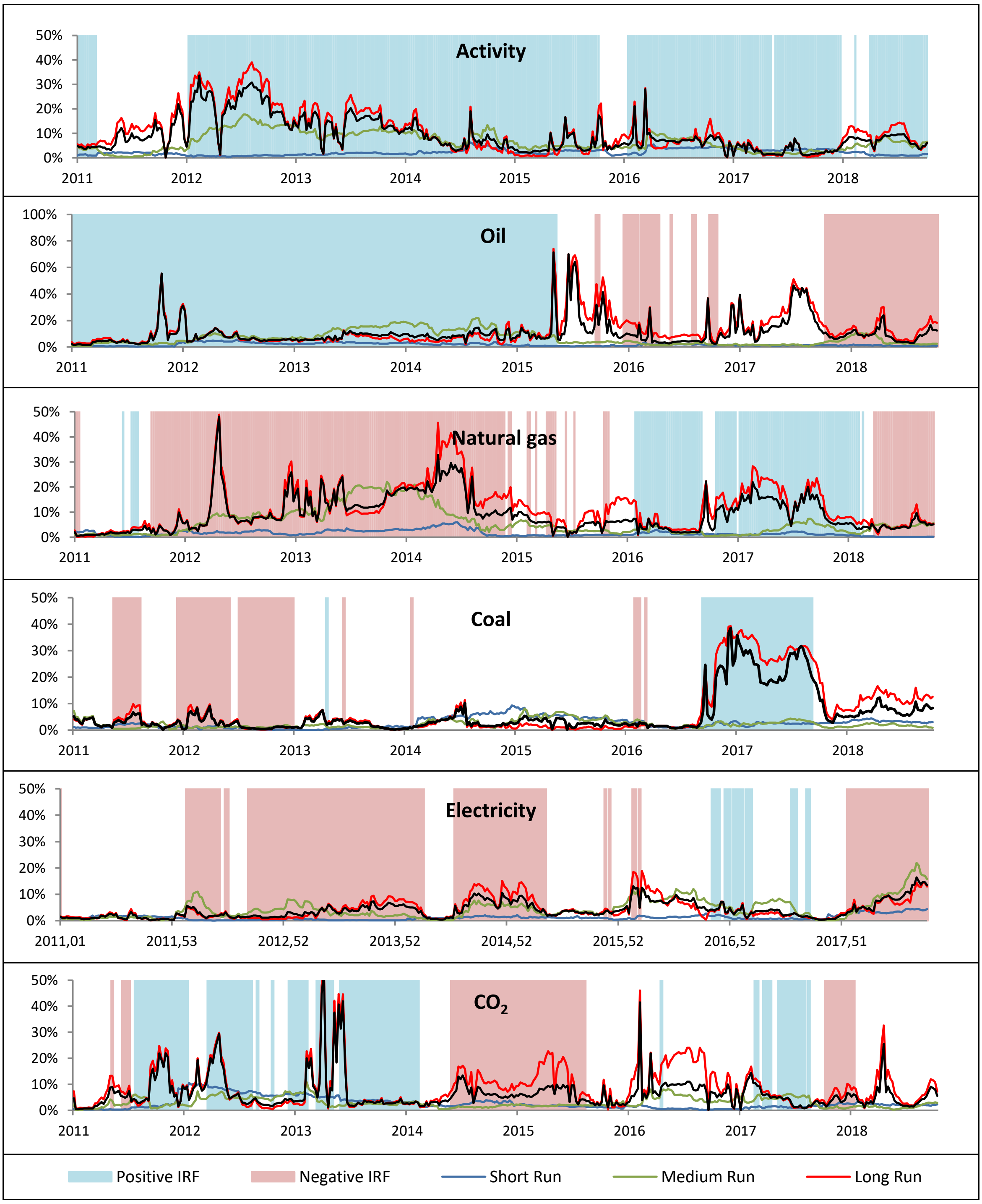
6.2.2. SFF: Connectedness from each model variable

Figure 7 reports the indices of pairwise connectedness to SFF from other variables of the model. Again, we do not report the decomposition of each pairwise index into its term components at different frequencies because the long-term component accounts for most of the index fluctuations, as it can be seen in Figure 6a. However, we report in each graph the connectedness created *within* the different frequency ranges to quantify the weight of each variable in explaining the fluctuations of the SFF at the corresponding band, with red, green and blue lines depicting the evolution of the long, medium and short-run *within* connectedness indices, correspondingly. As in Figure 5, we also report the sign of the responses of SFF to positive structural shocks. Blue areas indicate a positive response for at least four periods, following the contemporaneous zero response, while red areas indicate that the response of SFF remains negative for four weeks or more, as well following zero impact.[21]

Figure 7. Connectedness to SFF: total, short, medium and long-term components



[21] Note that the response of SFF to other shocks is zero on impact due to identification restrictions imposed.



The first panel of the figure depicts the pairwise connectedness to SFF from its own structural shock. We interpret this shock as the changes in the SFF unexplained by the other variables and include policy adjustments and omitted variables. The SFF shock explains around 55% of SFF variance. Interestingly, when we concentrate on the percentage of the high and medium-run fluctuations of the SFF, the percentage rises up to 90%, as demand fundamentals are basically emitters of long-run variance. Indeed, the fundamentals are not expected to impact SFF in short or medium run, as fundamental changes in SFF usually result from investment decisions, which are made on a basis of persistent changes on a market[22] and take time to be implemented[23]. Yet, even the percentage is high; the high-frequency fluctuations represent a negligible part of the SFF fluctuations by construction. Besides, we have normalized shocks to be positive thus the own SFF shock increases SFF by assumption.

An unexpected shock increasing economic activity induces a positive response of SSF, as is associated with more energy demand. Since renewable capacity in electricity production is fixed at short and medium-term, power stations have to use more fossil fuels to satisfy the demand. However, activity is becoming less and less important for SFF fluctuations, declining from a historical 20% to less than 10% in recent subsamples. This indicates that the economy does need fewer fossil fuels than before (in marginal terms) to expand by the same amount. We also find that activity is more important to explain low-frequency SFF fluctuations, indicating that the mechanism is structurally funded and indeed concerns changes in production structure and not short-term variations in production performance.

As Figure 7 shows, the response of the SFF to the oil shock is positive up to 2015 but reverses its sign thereafter. Interestingly, the importance of this shock for SFF fluctuations is also higher after 2015, increasing from an average of 8% to 15%. Note, that the sign of the response of SFF to the oil shock is a priory uncertain. As a proxy for the long-term natural gas price, we expect the oil price shock to decrease SFF, as

[22] Investors want to make sure that changes in prices are permanent and not temporary (or a policy indees will be implemented and enforced), as this directly impacts the opportunity cost of investment.

[23] A minimum construction time for RES is 6 month, being significantly longer for conventional power.

decreases the incentives to produce electricity with fossil fuels. However, at the same time, a higher price for oil product may raise demand for substitutes, and electricity among them, which in its turn leads to an increase in SFF.

According to our results, the second effect was dominating up to 2015, although with relatively small importance for SFF fluctuations. From this date on, and after a dramatic decrease in oil prices, the influence of the shock is larger, and the first effect appears to dominate, as the response of SFF becomes negative.

Besides, we find that transmission from the oil market helps to explain predominantly long-term SFF fluctuations, reflecting that oil-prices and investment decisions in renewable capacity are related through multiple channels.

The natural gas market is the largest contributor to SFF uncertainty, explaining around 9.2% of SFF fluctuations on average across subsamples. Yet, its importance has been markedly declining. This indicates that the fluctuations in natural gas hub prices do not currently generate so strong variations in the SFF, incentivizing switching to the more contaminating alternative coal when fossil fuels are required for electricity production by less than they used to do. As for the signs of the response of SFF, it is negative in most of the sample, consistent with unexpected increases in natural gas do not generate incentives to increase fossil fuel electricity production. Yet, the response of SFF to the natural gas shock depends also on indirect effects, as the natural gas is rival of electricity in the production process. Substitution between natural gas and electricity may explain the positive responses in some parts of the sample, such as in 2016-2017. Thus, a possible explanation for the opposite sign during this period is that electricity demand was increasing together with natural gas price, forcing the SFF to rise.

The natural gas shocks have little effect on SFF high and medium frequency movements because the amount of fossil fuels in electricity generation follows the amount of electricity generated with renewable sources, which is fixed at short. Therefore, transmission from natural gas is more important in the long-run, where generation capacity adjusts in accordance with the relative prices observed.

Shocks in coal prices explain less than 10% of the variation in SFF variable. The sign of the response of the SFF to a positive coal shock is either negative or neutral in most of the sample, consistent with decreasing incentives to produce electricity with coal. Between 2016 and 2017, however, the shock becomes more important, explaining about 35% of the SFF variation. Similar as we find for the natural gas shock, we observe a positive response of SFF to coal in this period. Again, this can be explained if electricity demand has been increasing together with coal (and natural gas) prices, forcing SFF to increase together with fossil fuel prices. Note that this explanation requires substitutability between coal, natural gas, and electricity in production. Like with natural gas, transmission from the coal market is more important for low-frequency SFF fluctuations as fossil fuel alternatives require time to be built.

The electricity market has little weight on SFF fluctuations. On average, the transmitted shocks from electricity account for about 4% of the SFF fluctuations. The signs of the response of SFF to the electricity market shock changes over time, which, together with the little importance of this shock in the SSF variance may indicate that their relationship is unstable. Note, however, that the market design for electric power in Europe is more consistent with a reversal relationship, from the SFF to electricity prices, and not the other way around. From the other side, sudden (unexpected) increases in the demand for electricity may raise both the electricity price and the SFF because renewable capacity is fixed in short. The contributions of electricity price to the long-term and the medium-term variances are about the same. This is likely to reflect the behavior of electricity traders, who are likely to take the SFF determinants as factors that help them to form their expectations, as well as a possible speculative component in their decision making.

The last plot in Figure 7 depicts the transmission to SFF from CO2 market shocks. In principle, an unexpected shock that raises the CO2 price makes fossil-fuel electricity generation more expensive, increasing the objectives of producers to switch to a cleaner energy source. Actually, this was the intended mechanism behind the design of the ETS and thus, the sign of this response can be used for the assessment of the ETS system. Up to 2015, the sign is usually the opposite, signaling that the mechanism was not worked as intended. Yet, up to the beginning of the current phase of the ETS, most of the permits for electricity generation were distributed from free. The sign after 2015 is mostly as expected, although in early 2017 the sign is positive. Note, however, that investment in clean energy plants takes time to be built, and any extra demand must be covered by fossil fuels generation.

Besides, we find that CO_2 market shocks explain a moderate share of the SFF variance (around 7%, on average) with periods of higher influence at the beginning of 2013 and 2016.

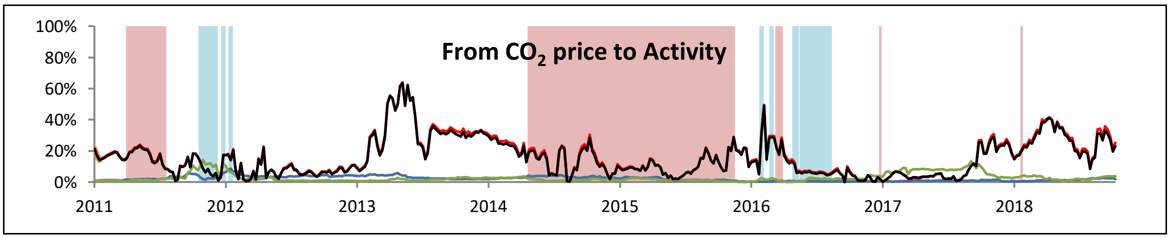
Summarizing the above, shock transmission from the components of the demand for permits explains a moderate share of SFF fluctuations, high during 2016-2017 although somewhat smaller in recent years. The most interesting result concerns transmission from the CO_2 prices. In spite of the relatively low weight of the CO_2 market-specific shock on the total SFF variance, it provides an exogenous source of variation, which allows us assessing the impacts of ETS. We find a positive response of SFF up to 2015. Thus our results are consistent with the view that the CO_2 price up to the first stages of Phase III was too low, signaling that the auctioning mechanism of permits was not working correctly. The sign of the response from 2015 is more consistent with the proper working of the ETS system, although in recent subsamples there also periods where we observe the positive relationship.

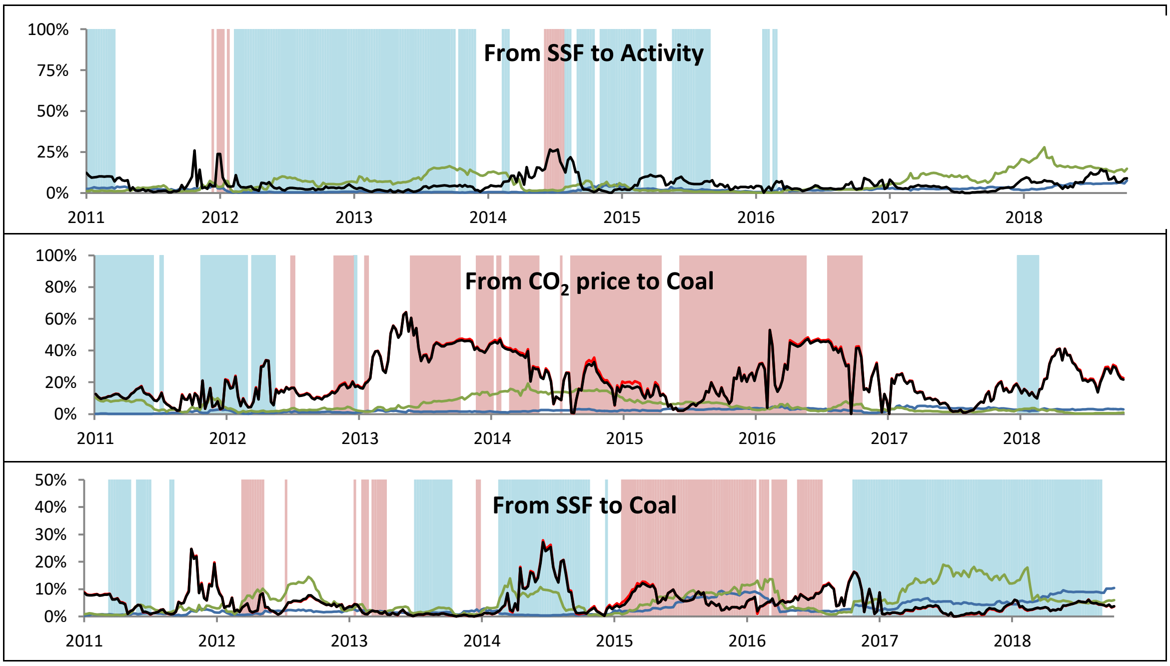
5.3. Other Results

In this section, we briefly comment other results of policy relevance that are also linked to the aims of the study.

The first plot in Figure 8 depicts the pairwise connectedness index from the CO_2 price to economic activity. Positive shock in the permit price induces negative responses in activity in most of the subsamples. However, from 2016 the sign of the response is usually not determined or even reversed, indicating that economic growth is now possible despite the increase of the permit prices. We depict the pairwise connectedness from SFF to economic activity in the second panel. As the figure shows, the positive relationship between SFF and economic activity has also vanished from 2016.

Figure 8. Additional results: pairwise and within frequency connectedness





Overall, the results in the first two panels of Figure 8 point towards the possibility of clean economic growth. Therefore the results here complement our previous finding on the declining importance of economic activity as a determinant of the CO_2 and the SSF fluctuations, suggesting that the nexus between activity and emissions is currently weaker in Europe, as argued in Cohen et al. (2018) or Wu et al. (2018).

The third and fourth panels of Figure 8 depicts the indices of pairwise connectedness from the CO_2 price and the SFF to the coal price, respectively. A positive permit price shock induces negative responses of coal price in most of the subsamples, as theory predicts. In recent periods, however, the sign response is not clearly determined, or even becomes positive, the overall importance of the shock declines. This result points out that the ETS is not very successful in reducing consumption of coal. As for the relationship between SFF and coal price, our results are in line with theory, at least in recent periods. Unexpected increases in the SFF imply higher demand for coal and raising its price. Yet, the importance of SFF in coal price fluctuations is currently small.

6. Conclusions

Our model and estimations provide a rich set of the empirical results, but we would like to highlight four following issues.

First, market fundamentals are important for the dynamics of CO2 prices. This means that just evaluating CO2 price and using it as a measure of overall effectiveness of ETS system is not completely correct. Understanding the source of CO2 price fluctuations is important for these interpretations. Understanding which market determinant is the most important at the moment for CO2 prices is helpful. The corresponding market can be used as an additional tool to help EU carbon market to function. Actually it is coal market that contributes the most to CO2 price variations, and is the most effective candidate to influence ETS prices.

Second, by concentrating on determinants of SFF fluctuations and the role of CO2 prices in it we suggest a convenient monitoring tool for ETS system. We still see that the impact of CO2 prices is limited. Instead, coal and natural gas markets are shown to be the most important determinants for SFF at the moment. This may serve as an indication of possible policy actions in this respect.

Third, our model provides strong evidence on decoupling of economic growth from fossil fuel and CO2 consumption. This directly connects to the goals of energy efficiency and carbon intensity. In this respect, out model provides a good monitoring tool for such objectives.

Fourth, we did not find very important connections on short and medium ranges, indicating that the role of expectations and speculation is not very important. However, this must be continuously monitored in the future, to be able to immediately detect possible market failures and correct them.

Some of our results have also interesting financial implications, as the CO_2 market is becoming largely financialized. For example, we show that the CO_2 price is strongly linked to oil or natural gas. However, these markets mostly contribute to the long-run fluctuations of the CO_2 price, but not to its high-frequency movements. Since we have shown that the relationship between these two commodities and the permit price is direct, our results imply that long-run investors in the carbon market are subject to substantial risk from oil and natural gas markets. For short-term traders, however, the risk is considerably lower, as the influence of these two commodities in the high-frequency fluctuations of the permit price is very small. Interestingly, the coal market seems to transmit uncertainty to the CO_2 price both at low and high frequencies. Consequently and reinforced by the fact that usually same investors operate on several energy markets, this market should be closely monitored by both long and short-term investors in the carbon market. These should take into account, however, that coal price shocks seem to induce negative CO_2 price responses.

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