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Carbon Financial Markets: a time-frequency analysis of CO_2 price drivers

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Abstract

We characterize the interrelation of CO_2 prices with energy prices (gas and electricity), and with economic activity. Previous studies have relied on time-domain techniques, such as Vector Auto-Regressions. In this study, we use multivariate wavelet analysis, which operates in the time-frequency domain. Wavelet analysis provides convenient tools to distinguish relations at particular frequencies and at particular time horizons. Our empirical approach has the potential to identify relations getting stronger and then disappearing over specific time intervals and frequencies. We are able to examine the coherency of these variables and lead-lag relations at different frequencies for the time periods in focus.

Keywords: Carbon prices; Financial Markets; Multivariate wavelet analysis.

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1 Introduction

The European Union Emission Trading Scheme (EU ETS) is the largest carbon market in the world, covering about 45% of greenhouse gas emissions from the European Union. It is a regional compromise by which EU countries are bonded to a total pre-set emissions for specific sectors, mainly energy and energy intensive industries. Under such scheme, the regulator, the European Commission, sets emission caps to be reached by the participants and enables them to trade emission permits in order to achieve the established cap: it is a cap-and-trade scheme.

Overall, the EU aims to reduce its emissions by 20% by 2020 compared to 1990, and by 40% by 2030. For this purpose the EU ETS contributes with a 21% cut in emissions in 2020 compared to 2005, in the sectors covered by the market. Although the EU ETS is the largest greenhouse gas (GHG) emission trading scheme in place, others exist in the USA, New Zealand, Japan, Australia, Canada, and in three cities in China. Carbon markets are a world accepted tool for climate change mitigation for they provide cost-efficient solutions. A few emission trading schemes more are under development.

The EU ETS was the first carbon market to be implemented. The first phase, for testing, took place between 2005 and 2007, the second, the Kyoto period, in 2008-2012, and the third, called post-Kyoto, is held since 2013 and will last until 2020. Despite meeting the emission reduction goals, the functioning of the European carbon market has raised some concerns. The main issue relates to the evidence of consistently low prices since Phase II until today, following the sharp fall of 2007, in the result of an overallocation of permits. In this context, it became evident the importance of understanding the origin of carbon prices and their impact on fossil fuels prices, main emitters of CO_2.

Initially, most of the research on carbon pricing used Granger causality methodology to find unidirectional relations between pairs of variables, including carbon and energy prices (Keppler and Mansanet-Bataller 2010; Creti *et al.* 2012). More recently, Vector Auto-Regressive (VAR) studies with multivariate analysis estimate impulse response functions that show the impact of innovations of a variable, namely carbon (Gorenflo 2012; Kumar *et al.* 2012; Aatola et al. 2013b). Also, in complement, there are studies on carbon price volatility (Aatola et al. 2013a; Byun and Cho 2013; García-Martos *et al.* 2013; Lutz *et al.* 2013).

We follow the previously referred studies and consider CO_2 prices interrelation with energy prices (gas, coal and electricity), and with economic activity index. These are the critical variables for carbon market actors. However, in this study we use multivariate wavelet analysis, to see how carbon prices behave at different frequencies and how this behavior changes over time. With data for the second and third EU ETS phases until today, the compulsory periods, our purpose in this paper is to identify relations getting stronger and then disappearing over specific time intervals and frequencies. With this approach, we are able to examine the coherency of these variables and lead-lag relations at different frequencies for the time period in focus.

The results we obtain are of particular relevance to market regulators, States and also emitting companies, because we provide a perception of the annual relationships between decision variables. This is different from the previous causality and impulse-response analysis, usually more pertinent for financial market players.

In the next section, we briefly describe the wavelet analysis tools. Section 3 describes our dataset. Section 4 presents results and Section 5 concludes.

2 Wavelet Analysis

Early applications of wavelets to economics were predominantly performed using some versions of the Discrete Wavelet Transform. These include, among others, the pioneering work of Ramsey and Lampart (1998a and 1998b) and Ramsey (1999), followed by Gençay *et al.* (2001a, 2001b and 2005), Wong *et al.* (2003), Fernandez (2005), Gallegati (2008), Gallegati *et al.* (2011), among several others. 10 years later, the literature using the Continuous Wavelet Transform (CWT) started to grow. Aguiar-Conraria, Azevedo and Soares (2008), Baubeau and Cazelles (2009), Rua and Nunes (2009), Rua (2012), Aguiar-Conraria and Soares (2011), Aguiar-Conraria, Martins and Soares (2012), Caraiani (2012), Fernández-Macho (2012), and

Kristoufek (2013) among several others, provide economic applications of these tools. Even in political science, CWT has been proven fruitful — e.g. see Alvarez-Ramirez et *al.* (2012) and Aguiar-Conraria, Magalhães and Soares (2012 and 2013).

We are not the first authors to use wavelets to analyze the energy markets or the relation between energy prices and other financial or macroeconomic variables. Actually, one can argue that wavelet analysis is particularly well suited for this purpose. Energy price dynamics are nonstationary and so it is important to use methods that do not require stationarity. Moreover, there is evidence showing that several energy markets display consistent nonlinear dependencies — Kyrtsou *et al.* (2009) . Based on their analysis, the authors call for nonlinear methods to analyze the impact of oil shocks. Wavelet analysis is one such method. Naccache (2011), Jammazi (2012) Vacha and Barunik (2012), Tiwari, Mutascu, Albulescu (2013), and Aloui and Hkiri (2014), among others, have already relied on wavelets to study the evolution of energy prices. Specifically about carbon markets there is no previous work performed in the time-frequency domain.

One common feature to all the above cited papers is that they rely on uni and bivariate wavelet analysis. So far multivariate wavelet analysis has never been applied to economic data. This is an important shortcoming, because when the association between two series is to be assessed, it is often important to account for the interaction with the other series. To estimate the interdependence, in the time-frequency domain, between two variables after eliminating the effect of other variables, we will rely on the concept of partial wavelet coherency and partial phase-difference.[1]

This section is necessarily brief. If interested in a detailed technical overview the reader can check Aguiar-Conraria and Soares (2013). We start by introducing some standard wavelet tools: (1) the wavelet power spectrum, which describes the evolution of the variance of a time-series at the different frequencies, with periods of large variance associated with periods of large power at the different scales, (2) the cross-wavelet power of two time-series, which describes the local covariance between the time-series, and the wavelet coherency,

[1] Fernández-Macho (2012) also proposes new statistical tools to determine the overall correlation for the whole multivariate set on a scale-by-scale basis.

which can be interpreted as a localized correlation coefficient in the time-frequency space, and (3) the phase, which can be viewed as the position in the cycle of the time-series as a function of frequency, and the phase-difference, which gives us information on the delay, or synchronization, between oscillations of the two time-series. The previous tools are standard, however they are important, because they will help us to describe the concepts of partial and multiple wavelet coherency and partial phase-difference, which are analogous to their bivariate counterparts, after controlling for the effects of other variables.

2.1 The Wavelet

For most of the applications, a wavelet ψ is a well localized function, both in the time domain and in the frequency domain, with zero mean, i.e. $\int_{-\infty}^{\infty} \psi(t)\, dt = 0$. This means that the function ψ has to wiggle up and down the $t-$axis, i.e. it must behave like a wave.

The specific wavelet we use is selected from the so-called *Morlet wavelet* family, first introduced in Goupillaud *et al.* (1984) and is:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i6t} e^{-\frac{t^2}{2}}. \tag{1}$$

The Morlet wavelet has an important property: it has optimal joint time-frequency concentration. The Heisenberg principle says that one cannot be simultaneously precise in the time and the frequency domain. Theoretically, the time–frequency resolution of the continuous wavelet transform is bounded by the so called Heisenberg box. The area of the Heisenberg box, which describes the trade-off relationship between time and frequency, is minimized with the choice of the Morlet wavelet. Another important characteristic is that it implies a very simple inverse relation between scale and frequency, allowing us to use the terms interchangeably.

2.1.1 The Continuous Wavelet Transform

Starting with a mother wavelet ψ, a family $\psi_{\tau,s}$ of "wavelet daughters" can be obtained by simply scaling and translating ψ:

$$\psi_{\tau,s}(t) := \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbb{R}, s \neq 0, \tag{2}$$

where s is a scaling or dilation factor that controls the width of the wavelet.

Given a time-series $x(t)$, its continuous wavelet transform (CWT) with respect to the wavelet ψ is a function of two variables, $W_x(\tau, s)$, obtained by "comparing" x with a whole family of wavelet daughters:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}}\overline{\psi}\left(\frac{t-\tau}{s}\right) dt, \tag{3}$$

where the bar denotes complex conjugation.

2.2 Univariate tools

2.2.1 The Wavelet Power and the Wavelet Phase

In analogy with the terminology used in the Fourier case, the (local) wavelet power spectrum (sometimes called scalogram or wavelet periodogram) is defined as

$$(WPS)_x(\tau, s) = |W_x(\tau, s)|^2. \tag{4}$$

This gives us a measure of the variance distribution of the time-series in the time-scale (time-frequency) plane.

When the wavelet $\psi(t)$ is chosen as a complex-valued function, as in our case, the wavelet transform $W_x(\tau, s)$ is also complex-valued and can be separated into its real part, $\Re(W_x)$, and imaginary part, $\Im(W_x)$, or in its amplitude, $|W_x(\tau, s)|$, and phase, $\phi_x(\tau, s) : W_x(\tau, s) = |W_x(\tau, s)| e^{i\phi_x(\tau,s)}$. Recall that the phase-angle $\phi_x(\tau, s)$ of the complex number $W_x(\tau, s)$ can be obtained from the formula: $\tan(\phi_x(\tau, s)) = \frac{\Im(W_x(\tau,s))}{\Re(W_x(\tau,s))}$, using the information on the signs of $\Re(W_x)$ and $\Im(W_x)$ to determine to which quadrant the angle belongs to.

2.3 Bivariate tools

In many applications, one is interested in detecting and quantifying relationships between two non-stationary time series. The concepts of cross-wavelet power, cross-wavelet coherency and wavelet phase-difference are natural generalizations of the basic wavelet analysis tools that enable us to deal with the time-frequency dependencies between two time-series.

The *cross-wavelet transform* of two time-series, $x(t)$ and $y(t)$, is defined as

$$W_{xy}\left(\tau, s\right) = W_x\left(\tau, s\right) \overline{W_y}\left(\tau, s\right), \tag{5}$$

where W_x and W_y are the wavelet transforms of x and y, respectively. We also define the *cross-wavelet power*, as $|W_{xy}(\tau, s)|$. For simplicity, in the next formulas we will omit (τ, s). The cross-wavelet power of two time-series depicts the local covariance between two time-series at each time and frequency. Therefore, cross-wavelet power gives us a quantified indication of the similarity of power between two time-series.

In analogy with the concept of coherency used in Fourier analysis, given $x(t)$ and $y(t)$ one can define their *complex wavelet coherency* ,ϱ_{xy}, by:

$$\varrho_{xy} = \frac{S\left(W_{xy}\right)}{\left[S\left(W_{xx}\right) S\left(W_{yy}\right)\right]^{1/2}}, \tag{6}$$

where S denotes a smoothing operator in both time and scale; as in the Fourier case, smoothing is necessary, otherwise coherency would be identically one.

The absolute value of ϱ_{xy} is the wavelet coherency: $R_{xy} = \left|\varrho_{xy}\right|$.

With a complex-valued wavelet, we can compute the phase of the wavelet transform of each series and thus obtain information about the possible delays of the oscillations of the two series as a function of time and scale (frequency), by computing the phase difference.

The phase difference can be computed from the cross-wavelet transform, by using the formula

$$\phi_{x,y} = \tan^{-1}\left(\frac{\Im\left(W_{xy}\right)}{\Re\left(W_{xy}\right)}\right). \tag{7}$$

Information on the signs of each part to completely determine the value of $\phi_{xy} \in [-\pi, \pi]$. A phase-difference of zero indicates that the time series move together at the specified frequency; if $\phi_{xy} \in (0, \frac{\pi}{2})$, then the series move in phase, but the time-series x leads y; if $\phi_{xy} \in (-\frac{\pi}{2}, 0)$, then it is y that is leading; a phase-difference of π (or $-\pi$) indicates an anti-phase relation; if $\phi_{xy} \in (\frac{\pi}{2}, \pi)$, then y is leading; time-series x is leading if $\phi_{xy} \in (-\pi, -\frac{\pi}{2})$.

2.4 Multivariate Tools

In this paper, we apply the concepts of multiple and partial coherency from Fourier spectral analysis into the context of wavelet time-frequency analysis — see Aguiar-Conraria and Soares (2013). We will display the formulae for the case of three variables. For more general cases, the reader is referred to the appendix of the aforementioned paper.

Given three series x, y, z, the *complex partial wavelet coherency* of x and y, after controlling for z, is given by the formula

$$\varrho_{xy\,.\boldsymbol{z}} = \frac{\varrho_{xy} - \varrho_{xz}\overline{\varrho}_{yz}}{\sqrt{(1 - R^2_{xz})(1 - R^2_{yz})}}. \tag{8}$$

Naturally, we define the *partial wavelet coherency,* $r_{xy\,.\boldsymbol{z}}$, as the absolute value of $\varrho_{xy\,.\boldsymbol{z}}$.

Having defined the complex partial wavelet coherency $\varrho_{xy\,.\boldsymbol{z}}$ between the series x and the series y, after removing the influence of z, we define the *partial phase-difference of* x over y, given z, as the angle of $\varrho_{xy\,.\boldsymbol{z}}$. We will denote this phase-difference by $\phi_{xy\,.z}$.

2.5 Statistical significance

There are some theoretical distributions that could be used for significance testing for the wavelet power spectrum — e.g. Torrence and Compo (1998) concluded that the wavelet power spectrum of an AR(0) or AR(1) process is reasonably well approximated by a chisquared distribution. Ge (2008), Cohen and Walden (2010) and Sheppard et al. (2012) have some important theoretical results on significance testing for the wavelet coherency. To our knowledge, no work has been done on significance testing for the partial coherency.[2]

All our significance tests are obtained using surrogates. To perform significance tests of wavelet measures, we fit an ARMA model to the series and construct new samples by drawing errors from a Gaussian distribution with a variance equal to that of the estimated error terms. For each time-series (or set of time-series) we perform the exercise 2000 times, and then extract the critical values at 5 and 10% significance.

Related to the phase-difference, there are no good statistical tests. This is so because it is very difficult to define the null hypothesis. In fact, Ge (2008) argues that one should not use significance tests for the phase-difference. Instead, one should complement its analysis by inspecting coherency, and only focus on phase-differences whose corresponding coherency is statistically significant.

3 Our Data

The European Union Emissions Trading System (EU ETS) is the first and the largest international system for trading greenhouse gas emission allowances. The time length of this study is 2008-2013, representing EU ETS Phase II (2008/2012) and one year of Phase III (2013-2020). As CO_2 variable we used the European Union Allowance (EUA) spot price, the unit of the EU ETS, referring to the emission of one tonne of CO_2 equivalent. Data for CO_2 was available from 2008/02/26 up to 2012/11/01, from Bluenext, the most important EUA spot market in volumes. From 2013/11/02 until 2013/11/12 prices were collected from SendeCO2.

Greenhouse gas emissions considered in the European carbon market come from fossil fuels burning. More than 11000 power stations, industrial plants and airlines, in Europe, operate under GHG emission limits. Hence, energy markets have an expected importance in the variations of CO_2 prices. We included prices for natural gas, coal and electricity in

[2] However, the method of Sheppard *et al.* (2012) may probably be extended for this case.

Europe as energy variables. For all, one month future contract was selected. This choice is in line with the established notion that energy future prices lead spot prices essentially due to the difficulty of storage and consequent ease of shorting.

Regarding natural gas prices, we used The Intercontinental Exchange Futures (The ICE) data. Originally in £/therm, the data was transformed to Euros/MMBTU for compatibility with other variables and better perception. As for coal, one month future prices were also retrieved from The ICE database. Coal prices are cost, insurance and freight (CIF) with delivery in Amsterdam, Rotterdam and Antwerp (ARA). They were originally in USD/tcoal and were converted to EUR/tcoal. For electricity, the Phelix baseload prices were retrieved from the European Energy Exchange (EEX), in Euros/MWh. The Phelix prices regard the German/Austrian market area. They were selected as representatives of the European base and peak electricity prices, because Germany is the largest electricity producer in Europe, which, combined with Austria, reached 680TWh of generated electricity in 2011. Also, correlation levels between Phelix data and other electricity prices (tested for France and UK) range from 0.87 to 0.95. Therefore, variations presented through Phelix prices should appropriately represent variations in other European electricity prices.

Noting that industries included in the EU ETS are energy intensive, and thus their production levels are highly associated with general economic growth, we considered necessary the inclusion of a variable which mirrored economic activity. This is in line with several previous authors in the subject (Alberola and Chevallier 2009; Alberola, Chevallier and Chèze 2009; Keppler and Mansanet-Bataller 2010). For this purpose we considered the daily price returns of FTS Eurofirst 300 Index (E3X.L), available at YahooFinance. It is a capitalization-weighted price tradable index measuring the performance of Europe's largest 300 companies.

4 Data Analysis

The several variables are depicted in Figure 1, on the left-hand side panel, together with their wavelet power spectrum, on the right-hand side. The wavelet power indicates, for each moment of time, the intensity of the variance of the time-series for each frequency of cyclical oscillations. This provides a first assessment of the behavior of each variable in the time-frequency domain.

Looking at Figure 1, it is interesting to note that the market for CO_2 is much less volatile than the other markets. Additionally, the periods of high volatility do not coincide. While markets for gas, electricity, coal and FTSE exhibit high levels of volatility until 2010, especially at 4 months frequencies (and also at longer run cycles, such as cycles with a periodicity of 20 months), volatility in the CO_2 market is only apparent after 2012 and, especially, during 2013, at very high frequencies. Based on the wavelet power spectra it is difficult to discern any interrelations between these markets.

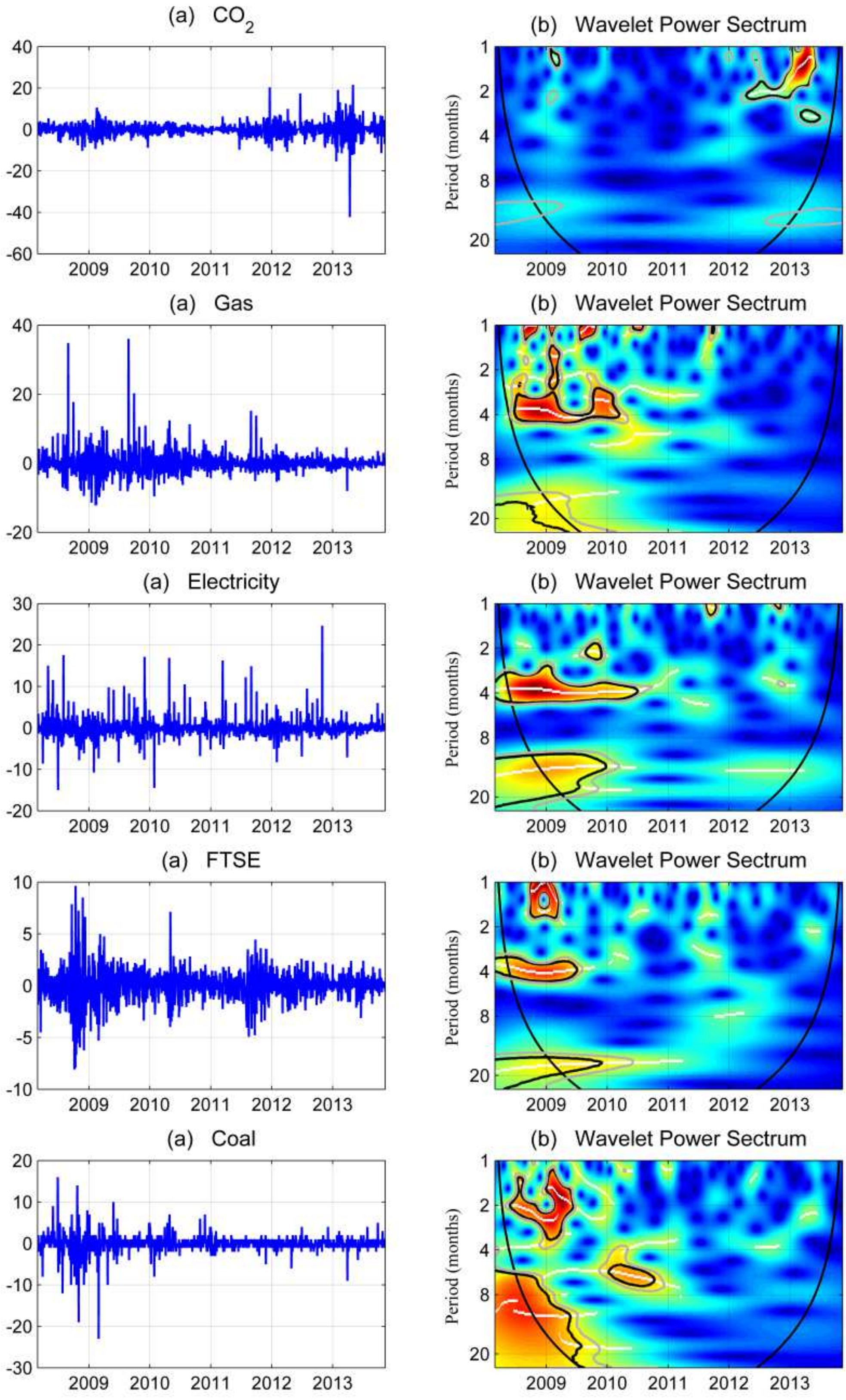

Figure 1: (a) Plot of the daily rate of return of each time-series. (b) The wavelet power spectrum. The black/grey contour designates the 5%/10% significance level. The cone of influence, which indicates the region affected by edge effects, is shown with a black line. The color code for power ranges from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum.

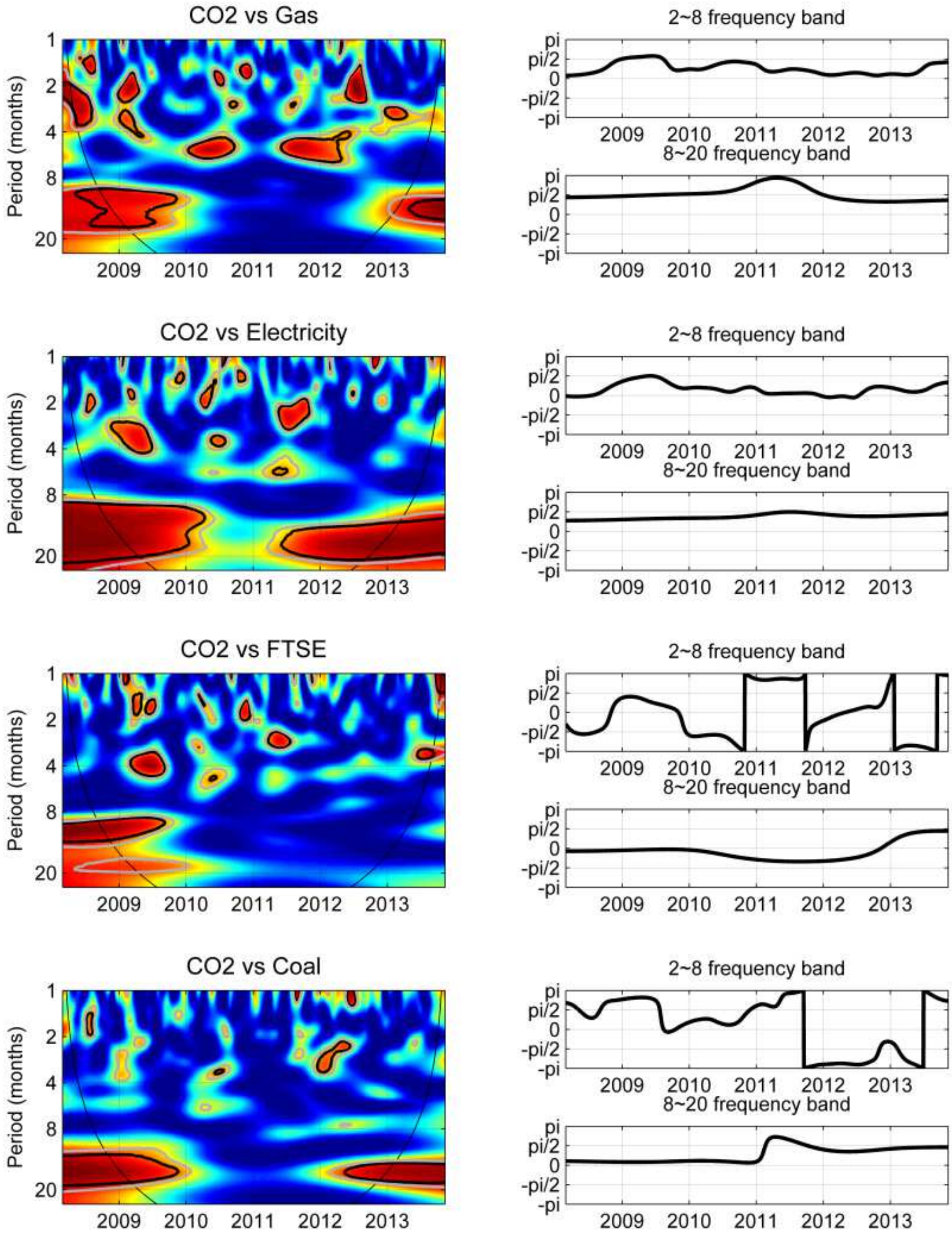

Figure 2: on the left — wavelet coherency. The thick/thin black contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency — close to zero) to red (high coherency — close to one). On the right — phase-differences between CO2 and another variable. Top: $2 \sim 8$ frequency band. Bottom: $8 \sim 20$ frequency band

In Figure 2, we estimate the coherency between CO_2 and the other variables. It is interesting to note that before 2010, at longer run frequencies (corresponding to cycles of periodicity between 8 and 20 months), we observe a statistically significant coherency. Looking at the phase-difference, and focusing in particular in the $8 \sim 20$ frequency band,[3] we observe very stable lead-lag relationships. The phase-difference between CO_2 and the energy variables is typically between 0 and $\pi/2$, indicating that the variables are in phase (positive correlation), with CO_2 leading. The phase-difference between CO_2 and FTSE is very close to zero, indicating an almost simultaneous relationship. If anything, the phase difference is slightly negative, suggesting that the leading variable is FTSE.

The relations described in the previous paragraph should not be taken as much more than descriptive statistics. In fact, when more than two series are given and the association between two of them is to be assessed, it is important to account for the interaction with the other series, otherwise one risks of incurring an omitted variable bias. To estimate the interdependence, in the time-frequency domain, between two variables after eliminating the effect of other variables, we rely on the concepts of partial coherency and partial phase-difference, described in the previous section.

In Figure 3, we have the partial coherency between CO_2 and each of the other variables, after controlling for all the others.

Comparing Figure 3 with Figure 2, we see that the results change somewhat and that not considering the partial coherency would lead us to erroneous conclusions. First, the relation between CO_2 and gas is almost nonexistent, once we control for the other variables. The other two variables that reflect energy markets exhibit quite different dynamics.

On the one hand, the region of (statistically significant) high partial coherency between CO_2 and Electricity is situated in the $8 \sim 20$ frequency band and is observable across most of the sample. For that frequency range, the partial phase-difference is consistently between 0 and $\pi/2$, which shows that the series move in-phase, with CO_2 leading.

On the other hand, partial coherency between CO_2 and Coal is stronger after 2011, especially after 2012. It is also interesting to note that this relation is also clearly visible at higher frequencies. Moreover, the partial phase-difference is very close to π at the lower

[3] It is difficult to attach any meaning to the phase-different in regions where coherency is not statistically significant. Therefore, we refrain from interpreting the phase-differences at the shorter run frequencies.

frequency band and it switches between $-\pi$ and π at higher frequencies. This shows that the variables are almost perfectly out-of-phase and that, if anything, coal is the leading variable along the $8 \sim 20$ frequency band.

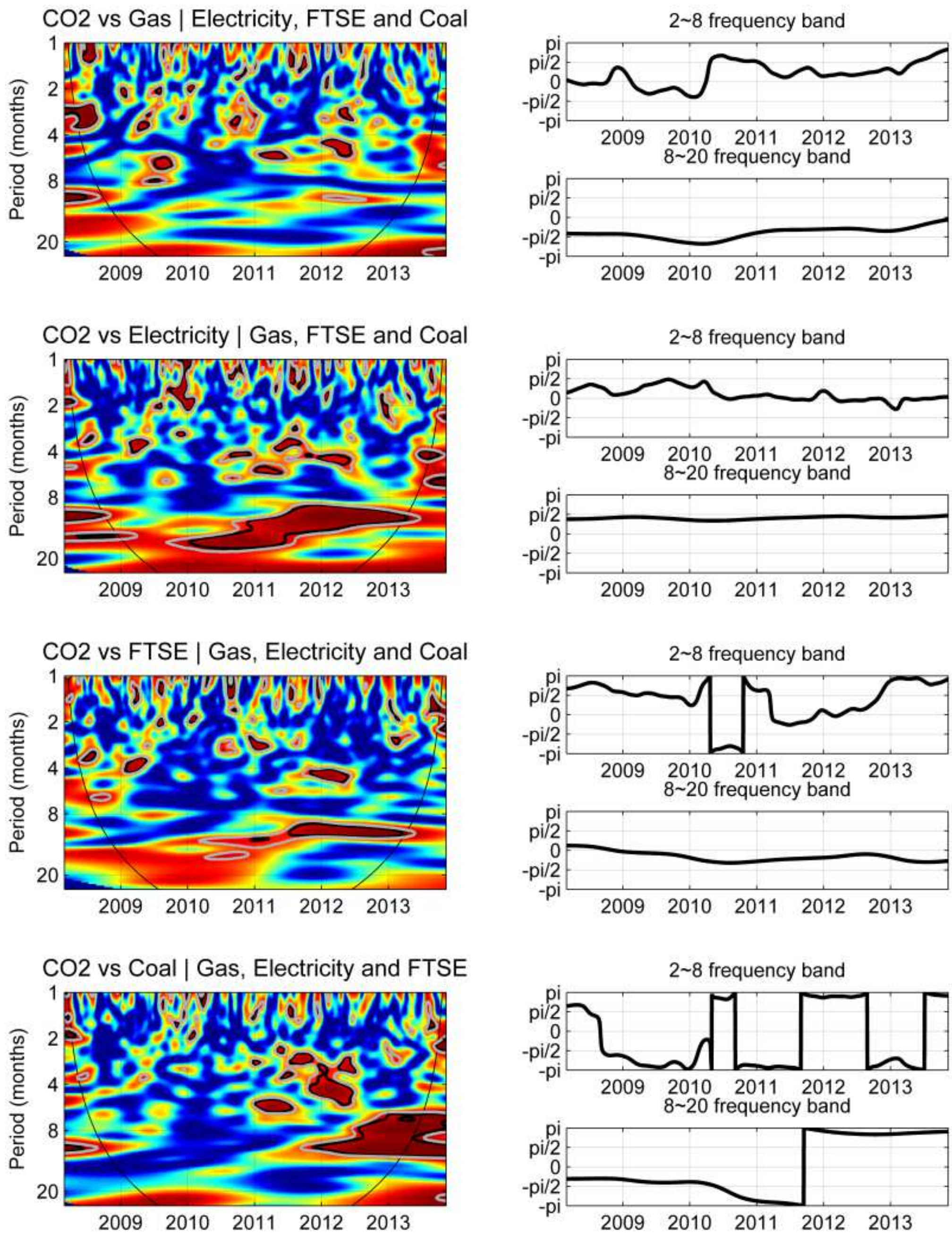

Figure 3: on the left — partial wavelet coherency. The black/grey contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency — close to zero) to red (high coherency — close to one). On the right — partial phase-differences between CO2 and the other variable. Top: $2 \sim 8$ frequency band. Bottom: $8 \sim 20$ frequency band

Finally, the partial coherency between CO_2 and economic activity, measured by FTSE, is particularly strong between late 2011 and early 2013, especially for cycles with periodicities slightly above 8 months. In this time-frequency range, the partial phase-difference is between $-\pi/2$ and 0, suggesting that the variables are in-phase, with CO_2 lagging FTSE.

5 Conclusions

In this paper we observed several situations relating carbon prices to energy prices that are consistent with a growing maturity of the European carbon market. We found evidence that, in cycles between 8 and 20 months, CO_2 and energy variables are correlated, with CO_2 leading, contributing to the accomplishment of the main objective of the market, which is to penalize emissions from fossil fuels.

Surprisingly we do not find a significant relation between CO_2 and gas in the time-cycles referred. Instead, we observed a high partial coherency between CO_2 and electricity, with CO_2 leading, and between CO_2 and coal, with coal leading. This result suggests that carbon pricing is having effects in the intermediate good, electricity, instead of on primary fuels, gas and coal. It seems that power suppliers are passing on the emission cost of using coal in their generation mix to the consumers through the electricity price. This is consistent with a low price demand elasticity of this good.

We also find higher volatility in carbon prices only after 2012, which may relate to the political uncertainties over the Post-Kyoto period, starting in 2013. At the same time, we observe that the carbon price follows the economy trends, in line with previous studies. This idea that carbon prices are capturing coal price information and reflecting it in electricity prices, allow us to conclude that the EU ETS is reaching stability and possibly overcoming its initial overallocation issues.

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