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Rita Sousa
Luís Aguiar-Conraria
Maria Joana Soares

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Carbon and Energy Prices: Surfing the Wavelets of California

Rita Sousa[*] Luís Aguiar-Conraria[†] Maria Joana Soares[‡]

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Abstract

Carbon price is a key variable in management and risk decisions in activities related to the burning of fossil fuels. Using innovative multivariate wavelet analysis, we study the link between carbon prices and primary and final energy prices in the time and frequency dimensions, particularly in longer cycles ($4 \sim 8$ and $8 \sim 20$ months).

We show a tight relation between carbon and electricity prices, co-moving together in one-year cycles, with electricity slightly leading, in opposition with previous results obtained for Europe. Thus, an over-allocation of allowances to the power generating sector is suggested. We also find indication of an out-of-phase relation between carbon and oil prices, with oil leading, and expect this relation to intensify when including fuel distributors in the CA market. Finally, and contrary to EU ETS previous results, we do not find a significant relation between carbon and economic activity.

In conclusion, although our results are not as significant as the ones previously obtained by other authors, for Europe, they show that the variables are related in the longer term, which supports the development of emissions trading in the post-2020.

Keywords: Carbon market; Energy prices; WCI; Multivariate wavelet analysis.

[*]Department of Economics, University of Minho, E-mail address: ritasousa@eeg.uminho.pt

[†]NIPE and Department of Economics, University of Minho, E-mail address: lfaguiar@eeg.uminho.pt.

[‡]NIPE and Department of Mathematics and Applications, University of Minho, E-mail address: jsoares@math.uminho.pt

1 Introduction

In the current economic uncertainty context, with climate change concerns, rise of primary energy prices, and numerous emission trading schemes multiplying around the world, there is an urge to develop quantitative tools to model and understand the origins of variations in carbon prices and effects in energy prices. Information on the movement of these variables has operational and political implications relevant to the main players in the market: polluters and regulators.

The emission trading scheme in California is one of the World's latest emerging greenhouse gas (GHG) market, created under the Assembly Bill 32 (AB32), as intended by the Western Climate Initiative (WCI), signed in 2007. It is an important instrument to meet the goal of reaching the state's 1990 GHG levels by 2020. Whereas there has been extensive research on carbon prices, built mainly on data from Europe, we present a first analysis of the California Carbon Allowances (CCA). Our aim in this paper is to evaluate dynamics in the time-frequency domain between CCA prices and other local energy prices, in these early stages, providing information for future periods, and comparing with European carbon market features.

This paper adds two important perspectives to current research. On the one hand, previous research on carbon markets proliferated after the launching of the European Emission Trading Scheme (EU ETS) phase I (2005) and focused on the study of the market itself, in aspects such as the sources of price variation, market design such as allocation or offsets role, volatility, etc. Few have analyzed both origins and implications of carbon prices in energy markets, and none is related to time-frequency issues. On the other hand, studies of the Californian carbon market have mostly focused on market design features (Fine et al. 2012, Sivaraman and Moore 2012, Burton et al. 2013, Thurber and Wolak 2013, Bushnell et al. 2014), although Bushnell (2007) looked into the impact on electricity prices. Therefore, this is an opportunity to test new market information.

On methodology, initial studies on carbon prices essentially explained the price or volatility of one variable in terms of others. They 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, new studies consider effects between variables — energy prices and carbon prices — in both directions. They include vector auto-regressive studies with multivariate analysis estimate impulse response functions that show the impact of innovations of a variable, namely carbon (Fezzi and Bunn 2009, Chevallier 2011a, Pinho and Madaleno 2011, Gorenflo 2012, Kumar et al. 2012, Aatola et al. 2013). Also, carbon price volatility, risk-premia and forecasting have lately been the focus of attention (Mansanet-Bataller and Soriano 2009, Chevallier and Sévi 2010, Chevallier 2011b, Feng et al. 2011, Rittler 2012, Byun and Cho 2013, Liu and Chen 2013, Lutz et al. 2013, Koch 2014, Medina et al. 2014, Reboredo 2014).

We follow the previous studies and consider CO_2 prices locally related to energy prices (in our case, gas, oil and electricity).[1] These are the critical variables for carbon market factors.

Like Sousa et al. (2014), to characterize carbon markets, we rely on multivariate wavelet analysis (MWA) and work in the time-frequency domain, estimating how carbon price relationships behave at different frequencies and how they evolve over time. We chose to work with MWA mainly for two reasons. First, it has been shown that energy price dynamics are strongly nonstationary and so it is important to use methods that do not require stationarity — Kyrtsou et al. (2009). Second, we note that changes in power supply quantities, on a large scale, are neither easy nor quick. Therefore, it makes sense to consider the presence of long-term decisions, or at lower frequencies, i.e., correlations in several temporal cycles. This can easily be done with wavelet analysis.

This paper proceeds as follows. Section 2 provides a description of the applied methodology, Section 3 describes the data used. Section 4 presents the empirical results, and Section 5 concludes and discuss some the policy implications of our results.

[1] We also included an economic activity index, but ended up excluding this variable, because of statistically insignificant results.

2 Multivariate wavelet analysis

Altough some authors have already relied on the use of wavelet analysis to study the evolution of energy prices, including oil, gasoline, natural gas, biofuels and other commodities (Naccache 2011, Jammazi 2012, Vacha and Barunik 2012, Tiwari, Mutascu and Albulescu 2013, Aloui and Hkiri 2014), as far as we know, specifically about carbon markets, the only previous work performed in the time-frequency domain is Sousa et al. (2014). With the exception of this recent paper by Sousa et al. (2014), one common feature to all the above cited papers is that they all rely on uni and bivariate wavelet analysis. So far, to the best of our knowledge, multivariate wavelet analysis is still very rare in economic or financial 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.

In this section we provide a necessarily brief description of the wavelet tools that we will apply. The reader proficient on wavelet analysis may skip this subsection without loss. The reader interested in an in-depth treatment is directed to Aguiar-Conraria and Soares (2014). The reader looking for a nontechnical, yet very complete, explanation of these concepts is referred to Aguiar-Conraria et al. (2012 and 2013).

2.1 The origins of the wavelet and of the Continuous Wavelet Transform

The theory behind wavelet analysis can be traced back to 1807, when Joseph Fourier showed that almost any periodic function could be written as a weighted sum of sines and cosines of different frequencies. Even if the function is not periodic, under some conditions, it still may be expressed as an integral of sines and cosines multiplied by a weighting function. It takes one step to apply these ideas to study cycles in time-series data. The typical approach is to map the original variable, say x_t, into the frequency domain, by means of the Fourier transform.

Fourier spectral analysis has been used to estimate which cycles play predominant roles in explaining the variance of a time-series. For example, Granger (1966) and King and Watson (1996) used these techniques to identify some stylized business cycle facts, Nerlove (1964) and Wen (2002) used them to identify seasonal components and Merrill, Grofman, and Brunell (2008) relied on this technique to estimate predominant cycles in the North American national election results.

In the literature, there are several slight variations in the definition of Fourier transform. Here, we adopt the following convention for the Fourier transform, $X(\omega)$, of a given square integrable function x_t: [2]

$$X(\omega) = \int_{-\infty}^{\infty} x_t \left[e^{-i\omega t}\right] dt. \tag{1}$$

The spectral representation of a function given by its Fourier transform determines all the spectral components embedded in the function. The main limitation of Fourier analysis is apparent in the above formula, where X is a function only of ω, the frequency, implying that the information about time is lost under the Fourier transform. To overcome this problem, Denis Gabor, the Hungarian-born Nobel laureate in physics, proposed in his fundamental paper on communication theory — Gabor (1946) — the use of a modified version of the Fourier transform, which became known as the short time Fourier transform. The idea is simple: we first choose a window function g, i.e. a well localized function in time, in order to localize the Fourier analysis. Then we shift the window along the t-axis. Mathematically, we multiply the function x_t by translated copies of g to select "local sections" of x_t, whose Fourier transforms are then computed. We thus obtain a function of two-variables, τ (the translation parameter) and ω (the angular frequency), given by $G_{g,x}(\tau, \omega) = \int_{-\infty}^{\infty} x_t \left[\overline{g}(t-\tau)\, e^{-i\omega t}\right] dt$, where the over-bar denotes complex conjugation.

Gabor (1946) used Gaussian functions as windows. For that particular case, the short time Fourier transform is known as the Gabor transform. The principal limitation of this technique is that it gives us a fixed resolution over the entire time-frequency plane. In fact,

[2] With this definition, ω is the *angular* (or radian) frequency. The relation to the more common Fourier frequency is given by $f = \frac{\omega}{2\pi}$.

the functions $g_{\tau,\omega}(t) = g(t-\tau)e^{-i\omega t}$, being obtained by simple translations in time and modulations (i.e. translations in frequency) of the window function g, all have the same "size" as g.

Kahane and Lemarié-Rieusset (1995) and Daubechies (1996) tell us how the struggle with these limitations paved the way for wavelet analysis. It happened in late 1970s, while Jean Morlet was working for an oil company. His work consisted in analyzing how one could generate acoustic waves at the surface and then record the reflected waves. With that information, he would estimate the influence of each layer of soil by checking the frequency of the reflected waves. Morlet was unhappy with the Gabor time-frequency analysis: at high frequencies, there were too many oscillations (leading to numerical instability) and there were not enough oscillations at low frequencies. Morlet could have applied the Gabor transform with a narrow window to study high frequency components and a wide window to analyze low frequency components. However, Morlet wanted to be able to do both simultaneously with one single transform. To solve this problem, Morlet modified the Gabor approach by using dilation, instead of modulation. The idea is to consider a window which is an oscillatory function — hence can be seen as a function with a certain frequency — and compress it in time to obtain a higher frequency function or spread it out to obtain a lower frequency function. And, of course, these functions could be shifted in time. Therefore, the transform function depends on two parameters, one that captures the time location and another that captures the degree of compression or scale.

Mathematically, $g_{\tau,\omega}(t)$ is replaced by a two-parameter family of functions, $\psi_{\tau,s}(t)$, which we call the wavelet daughters. In this case, however, the functions $\psi_{\tau,s}(t)$ are obtained from a given window function $\psi(t)$, which is oscillatory — the so-called mother wavelet —, by a dilation by a scaling (or compressing) factor s and a translation by τ,

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s,\tau \in \mathbb{R}, s \neq 0.^3. \tag{2}$$

For $|s| > 1$, the windows $\psi_{\tau,s}$ become larger (hence, correspond to functions with lower

[3]The factor $1/\sqrt{|s|}$ is a normalizing factor being introduced so that all the wavelet-daughters have the same energy as the mother wavelet, where the energy of a function x_t is given by $\int_{-\infty}^{\infty}|x_t|^2dt$.

frequency) and for $|s| < 1$, the windows become narrower (hence, become functions with higher frequency). The main advantage of the wavelet transform, as opposed to the Gabor transform, is clear: instead of giving a fixed resolution over the entire time-frequency plane, it provides us a time-scale (or time-frequency, as we will explain later) representation of a function with windows whose size automatically adjusts to frequencies: it stretches into a long wavelet function to measure the low frequency movements; and it compresses into a short wavelet function to measure the high frequency movements.

Jean Morlet was an engineer. He realized that this new approach worked quite well in practice, but he was not able to explain why. Daubechies (1996) quotes Morlet's description of his audiences reaction: "If it were true, then it would be in the math books. Since it isn't there, it is probably worthless." Thanks to a common friend, Morlet approached Alex Grossmann, a quantum physicist, who related the Morlet wavelet transform to some areas of study in quantum physics. In 1984, the engineer Jean Morlet, the quantum physicist Alex Grossmann and the geophysicist Pierre Goupillaud — Goupillaud, Grossmann and Morlet (1984) — provided the first formalization of the continuous wavelet transform.[4] The definition of the continuous wavelet transform is similar to the short time Fourier transform. Simply replace the window functions $g_{\tau,\omega}$ by the wavelet daughters $\psi_{\tau,s}$. Given a time-series $x(t)$, its continuous wavelet transform (CWT) with respect to the wavelet ψ is a function of two variables, $W_x(\tau, s)$, defined by

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

Compare formulas (1) with (3). In the Fourier transform, X is only a function of ω, the frequency,hence the information about time is lost under this transform. This implies that, while one can use Fourier analysis to extract information about the periodicity/frequency of the most important cycles, it will be virtually impossible to tell when those cycles occur and to trace changes in their behavior. In the continuous wavelet transform, the position of the wavelet in time is given by τ, while its position in the scale is given by s. Therefore

[4] Previously, Morlet had only worked with a discrete choice of scales.

the wavelet transform, by mapping the original series into a function of two variables, τ and s, gives us information simultaneously on time and scale, which is equivalent to providing information simultaneously on time and frequency.

The minimum requirements imposed on a function ψ to qualify for being a mother wavelet are that ψ is a square integrable function and also that it fulfills a technical condition, usually referred to as the *admissibility condition*.

For most of the applications, the wavelet ψ must be a well localized function, both in the time domain and in the frequency domain, in which case the admissibility condition reduces to requiring that ψ has 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; this, together with the assumed decaying property justifies the choice of the term wavelet to designate ψ.

The specific wavelet we use in this paper is a complex-valued function selected from the so-called *Morlet wavelet* family, first introduced in Goupillaud et al. (1984):

$$\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}, \tag{4}$$

and corresponds to the particular choice of $\omega_0 = 6$. Although, strictly speaking the above function is not a true wavelet, since it has no zero mean, for sufficiently large ω_0, namely for the value used in this paper, $\omega_0 = 6$, for all numerical purposes it can be considered as a wavelet; see Foufoula-Georgiou and Kumar (1994).

The popularity of the Morlet wavelets is due to their interesting characteristics. Since ψ_{ω_0} is simply a complex sinusoid of angular frequency ω_0 damped by a Gaussian “envelope", it is reasonable to associate the angular frequency ω_0 — i.e. the usual Fourier frequency $f = \omega_0/(2\pi)$ — to this function; hence, the wavelets at scale s can be associated with frequencies $f_s = \frac{\omega_0}{2\pi s}$; for $\omega_0 = 6$, we have $f_s \approx \frac{1}{s}$, which greatly facilitates the interpretation of the wavelet analysis — which is a time-scale analysis — as a time-frequency analysis. Also, this function inherits, from its Gaussian envelope, an important property: it has optimal joint time-frequency concentration. The Heisenberg principle says that one cannot be simultaneously precise in the time and in the frequency domains. Theoretically, the time-frequency resolution of the wavelet 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.

2.2 Wavelet tools

Remark 1 *As for the wavelet transform, all the quantities we are going to introduce below are functions of two variables, time (τ) and scale/frequency (s). To simplify the notation, we will describe these quantities for specific values of the arguments which, unless strictly necessary, will be omitted from the formulas.*

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*, denoted by $(WPS)_x$, is defined as

$$(WPS)_x = |W_x|^2 . \tag{5}$$

The wavelet power spectrum (sometimes called *scalogram* ot *wavelet periodogram*) 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 is also complex-valued and can, therefore be separated into its real part, $\Re(W_x)$, and imaginary part, $\Im(W_x)$; alternatively, the transform can be expressed in polar form as

$$W_x = |W_x| \, e^{i\phi_x}, \;\; \phi_x \in (-\pi, \pi].$$

The angle ϕ_x is known as the *(wavelet) phase.*[5] For real-valued wavelet functions, the imaginary part is zero and the phase is undefined. Therefore, to separate the phase and amplitude

[5] Recall that the phase-angle ϕ_x of the complex number W_x can be obtained from the formula: $\tan(\phi_x = \frac{\Im(W_x)}{\Re(W_x)}$, using the information on the signs of $\Re(W_x)$ and $\Im(W_x)$ to determine to which quadrant the angle belongs to.

information of a time-series, it is necessary to use complex wavelets.

2.3 Coherency and phase-difference

In many applications, one is interested in detecting and quantifying the time-frequency relations between two non-stationary time series. Generalizations of the wavelet tools, appropriate for this purpose, are now briefly described.

Given two time-series, $x(t)$ and $y(t)$, we define their *cross-wavelet transform*, W_{xy}, by

$$W_{xy} = W_x \overline{W_y} \tag{6}$$

where W_x and W_y are the wavelet transforms of x and y, respectively. The absolute value of the cross-wavelet transform, $|W_{xy}|$, will be referred to as the *cross-wavelet power*.

We also define the *complex wavelet coherency* of x and y, ϱ_{xy}, by

$$\varrho_{xy} = \frac{S\left(W_{xy}\right)}{\left[S\left(|W_x|^2\right) S\left(|W_y|^2\right)\right]^{1/2}}, \tag{7}$$

where S denotes a smoothing operator in both time and scale.[6] By analogy with the Fourier case, the *wavelet coherency*, R_{xy}, is defined simply as the absolute value of the complex wavelet coherency, i.e.

$$R_{xy} = \frac{\left|S\left(W_{xy}\right)\right|}{\left[S\left(|W_x|^2\right) S\left(|W_y|^2\right)\right]^{1/2}}, \tag{8}$$

With a complex-valued wavelet, we can compute the wavelet phases of both series and, by computing their difference, we are able obtain information about the possible delays of the oscillations of the two series, as a function of time and frequency. It follows immediately from (6) that the phase-difference, which we will denote by ϕ_{xy}, can also be computed simply as the phase-angle of the cross-wavelet transform, i.e. by using the formula

$$\tan \phi_{x,y} = \frac{\Im\left(W_{xy}\right)}{\Re\left(W_{xy}\right)},$$

[6] As in the Fourier case, smoothing is necessary, otherwise the magnitude of coherency would be identically one.

together with the 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 indicates an anti-phase relation; if $\phi_{xy} \in (\frac{\pi}{2}, \pi)$, then y is leading; time-series x is leading if $\phi_{xy} \in (-\pi, -\frac{\pi}{2})$.

Remark 2 *The wavelet-phase difference is sometimes defined as the phase-angle of the complex wavelet coherency; although this is not fully consistent with the difference between the individual phases, since it is affected by the smoothing, the results obtained are not substantially different; this alternative definition has the advantage of being simpler to generalize to the multivariate case.*

2.4 Multivariate tools: partial coherency and partial phase-difference

Some wavelet tools specially designed to use when more than two series are involved, namely the so-called partial wavelet coherency and partial phase-difference, have recently been introduced; see, e.g. Mihanović et al. (2009) for the case of three series and Aguiar-Conraria and Soares (2014) for the more general case. Here, we will only display the formulas for the case of three variables. For the other cases, the reader is referred to the appendix of the aforementioned paper by Aguiar-Conraria and Soares (2014).

Given three series x, y, z, we define the *complex partial wavelet coherency* of x and y after controlling for z, denoted by by $\varrho_{xy\,.\boldsymbol{z}}$, the quantity given by

$$\varrho_{xy\,.z} = \frac{\varrho_{xy} - \varrho_{xz}\overline{\varrho_{yz}}}{\sqrt{(1 - R_{xz}^2)(1 - R_{yz}^2)}}. \tag{9}$$

We then define the *partial wavelet coherency*, $R_{xy\,.z}$, as the absolute value of the complex partial wavelet coherency, and the *partial phase-difference* of x over y, given z, denoted by $\phi_{xy\,.z}$, as the phase-angle of $\varrho_{xy\,.z}$.

2.5 Statistical significance

Naturally, it is important to assess the statistical significance of the computed wavelet measures. Torrence and Compo, in their influential paper — Torrence and Compo (1998) — were among the first authors to discuss this issue. Based on a large number of Monte Carlo simulations, Torrence and Compo concluded that the wavelet power spectrum of a white or red noise process, normalized by the variance of the time-series, is well approximated by a chi-squared distribution. This problem was reconsidered more recently by Zhang and Moore (2012). For the specific case of the use of a wavelet ψ_{ω_0} from the Morlet family, Zhang and Moore established, analytically, that the wavelet power spectrum of a Gaussian white noise with variance σ^2 is distributed as

$$|W_x|^2 \frown \frac{\sigma^2}{2}(1+e^{-\omega_0^2})X_1^2 + \frac{\sigma^2}{2}(1-e^{-\omega_0^2})X_2^2 \,,$$

where X_1 and X_2 are independent standard Gaussian distributions. In the case of a Morlet wavelet with parameter $\omega_0 > 5$, we have $e^{-\omega_0^2} \approx 0$, and so we obtain $\left|\frac{W_x^2}{\sigma^2}\right| \frown \frac{1}{2}\chi_2^2$, confirming, for this specific type of wavelet and particular underlying process, the result obtained by Torrence and Compo. To assess significance of the wavelet power spectrum we will rely on this theoretical distribution

Ge (2008), Cohen and Walden (2010, 2011) and Sheppard et al. (2012) have some important theoretical results on significance testing for the wavelet coherency. The results, however, are for specific ways of smoothing (namely in the time domain only) and do not apply directly to our case. To our knowledge, no work has been done on significance testing for the partial coherency. All our significance tests are obtained using surrogates. We fit an ARMA(1,1) 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 5000 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 the coherence, and only focus on phase-differences whose corresponding coherence is statistically significant.

3 A first look at our data: energy and carbon prices

The carbon market in California (called WCI for simplification) took effect in early 2012 and is linked to Québec's since January 2014. It is undergoing its first period — 2012-2014 (compliance started in 2013); second compliance period starts in 2015, and will last until 2017, including distributors of transportation fuels, natural gas, and other fuels; and finally 2018-2020 will cover the third period. Currently, prospects for post-2020 and linkage to Mexico's carbon pricing are being considered.

California (CA) is one of the largest economies in the world. On energy, in 2011 the state had a consumption of 7858,4 trillion BTU and produced internally around 2624,5 trillion BTU of primary energy (crude oil and natural gas accounting for 43% and 11%, respectively, 15% coming from nuclear electric power and 32% from renewables). California's electricity system generates more than 200,000 GWh per year. The current source shares include approximately 63% natural gas, 9% hydroelectric, 18% other renewables, 9% nuclear and 1% coal. In fact, California produces 70% of the electricity it uses. The state imports the remaining amount.[7] California challenge on electricity under AB32 is to secure supply with 33% renewable sources, while reducing greenhouse gases (GHG) emissions. In consequence, California emitted of a total of 448 MMTCO2eq. (million metric tonnes of CO_2 equivalent) in 2011, from which 38% originated from transportation, 23% from industrial sources and 19% from electricity generation (10% imported plus 9% in state).[8] As noted in AB32, California has an emission goal of 427 MMTCO2e in 2020, i.e. equaling 1990 estimated emissions, and aims to an 80% reduction in 2050 below 1990 levels.

California Carbon Allowances, or CCAs, are traded in the Intercontinental Futures Ex-

[7] Electricity data from 2012 retrieved from CA Energy Almanac, 8th January 2014, http://energyalmanac.ca.gov/electricity.

[8] California's Greenhouse Gas Inventory official page: http://www.arb.ca.gov/cc/inventory/data/data.htm.

change US (The ICE Futures US),[9] a leading trade for commodity markets. Currently, traded products are CCAs Vintage Futures for 2013-2016, and corresponding options on futures.

An important difference between the California market and the European Emission Trading Scheme (EU ETS) regards the inclusion of importers of electricity from out of state (through its primary energy source mix), and of distributors of transportation fuels, natural gas, and other fuels , that do not exist in Europe. All other CA trading sectors [10] are, in their essence, energy intensive and/or high emission sectors, such as the EU sectors. Considering these WCI market fundamentals and other previous work on European CO_2 prices causality (Alberola et al. 2009, Fezzi and Bunn 2009, Keppler and Mansanet-Bataller 2010, Sijm et al. 2012, Aatola et al. 2013, Lutz et al. 2013, Nazifi 2013) our model initially considered six variables associated to the energy and carbon markets in California: CO_2 price (CCA), electricity, gas and oil prices and an economic activity index — Dow Jones Utility Index, DJU. We dropped the economic activity index due to insignificant results.

CO_2

In this study, we used the available daily series on the CCA Future Vintage 2013 and 2014 released by Climate Policy Initiative S. Francisco of The ICE data. Data was available from 29/08/2011, and 766 observations were included, without missing information. Average value was of 14,21 US$ per CCA, reaching a maximum level of 23,75 US$ and a minimum of 11,55 US$ per CCA, visible in Figure 1. The limits on US$ axis are intentional 10 and 40 US$, for these are the expected CCA price thresholds. 10US $ is the minimum CCA value at auctions and 40 US$ is the minimum price of CCAs from the strategic price containment reserve.

[9]CCA at The ICE: https://www.theice.com/productguide/ProductSpec.shtml?specId=6747556#.

[10]Sectors included in AB32 carbon trading since 2013 are: first deliverers of electricity (in-state and imported) and large industrial facilities (such as petroleum refineries; crude petroleum and natural gas extraction; cement; industrial gas; mineral mining and lime; fruit and vegetable canning; glass; paper; dairies; iron, steel, and aluminium; chemical, biological, and pharmaceutical; breweries, wineries, and juice). After 2015, distributors of transportation fuels, natural gas, and other fuels will also be included. In: http://www.arb.ca.gov/cc/capandtrade/allowanceallocation/allowanceallocation.htm.

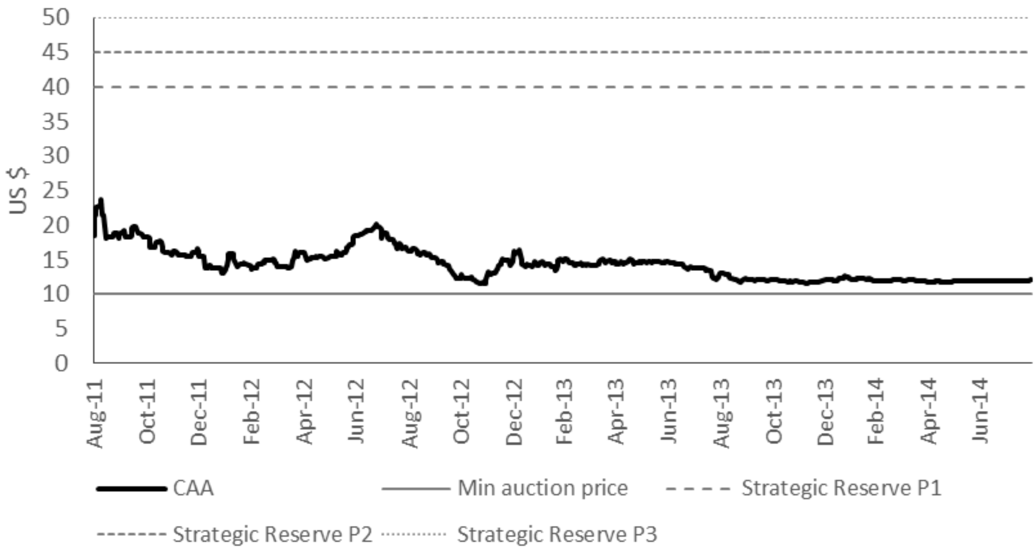

Figure 1: California carbon prices, 2011–2014
(Data source: The ICE, retrieved from CPI, California Carbon Dashboard, http://calcarbondash.org/)

Energy

The AB32 program covers nearly 600 emitting facilities, responsible for 85% of CA emissions. Phase one includes electric utilities and large industrial facilities that emit more than 25 MtCO2/year, and in phase two, distributors of transportation, natural gas and other fuels will also be added. We include in this category representative electricity prices, oil, natural gas and gasoline prices. Coal was not included due to its small percentage in the generation mix of California.

Regarding the electricity variable, we considered the wholesale day ahead price of SP15 EZ Generation Hub, located in California. Data source is The ICE exchange. It was retrieved from the US Energy Information Association (EIA) information page for ten major electricity trading hubs in USA.[11] Prices are in US$/MWh and were included from 29/08/2011 to 29/08/2014, with only 30 days of missing data.

[11] EIA electricity data: http://www.eia.gov/electricity/data/browser/.

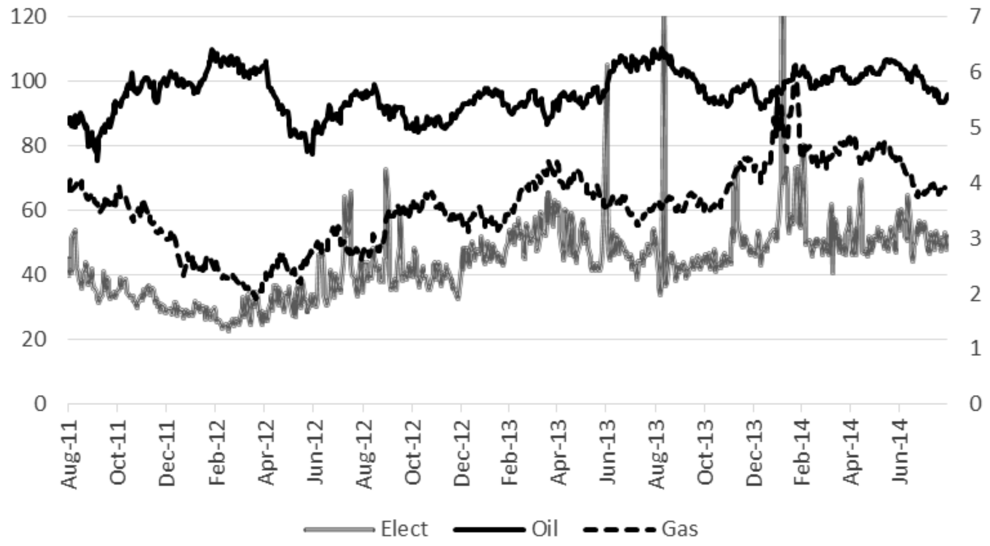

Figure 2: California selected energy prices, 2011–2013
(On the left vertical axis we refer to electricity and oil prices. The right axis refers to gas prices. Data sources: referred in text.)

Oil prices regard the West Texas Intermediate (WTI) Light Sweet Crude Oil Futures (one month future), exchanged and available at The ICE, at US$ per US barrel ($/USbbl). No missing data.

For natural gas prices we used Natural Gas Futures Contract 1 (Dollars per MillionBTU - MMBTU), or front month futures, available from the US Energy Information Association (EIA).[12] The source is the New York Mercantile Exchange (NYMEX) and the prices are based on delivery at the Henry Hub in Louisiana. Minor missing data (20 days) for the time length considered, totalizing 753 observations.

In Figure 2, we can see the evolution of energy prices. Like in the previous section, we did not consider variables as the Clean Dark and Spark Spreads, or the “carbon switch" because they are linear combinations of variables included.

[12] EIA natural gas data: http://tonto.eia.gov/dnav/ng/hist/rngc1d.htm.

4 Data Analysis

Figure 3 provides a first assessment of the behavior of each variable in the time-frequency domain. Variables are plotted 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. It is interesting to note that the electricity prices are much less volatile than the other prices, with the blue color dominating most of the picture.

In the case of carbon prices, most of the volatility is observed before early 2013, and it is especially strong in the second half of 2012, period in which the wavelet power spectrum is statistically significant simultaneously at several frequencies. It is also worth referring that there is a statistically significant cycle, with period of about 12 months, that runs from the beginning of the sample until the first quarter of 2013.

The case of the other energy prices, gas and oil, is interesting. There are regions of warm colors, both at several frequencies and several periods of time, but only one is statistically significant in each primary energy. In the case of gas, the main significant region happens at high frequencies and slightly before mid-2012. In the case of oil, the statistically significant region occurs for most of 2012 (and runs until early 2013) and is concentrated in the frequencies that correspond to cycles of periods of about four to six months.

Based on this preliminary analysis of the wavelet power spectra it is difficult to discern any inter-relations between these markets.

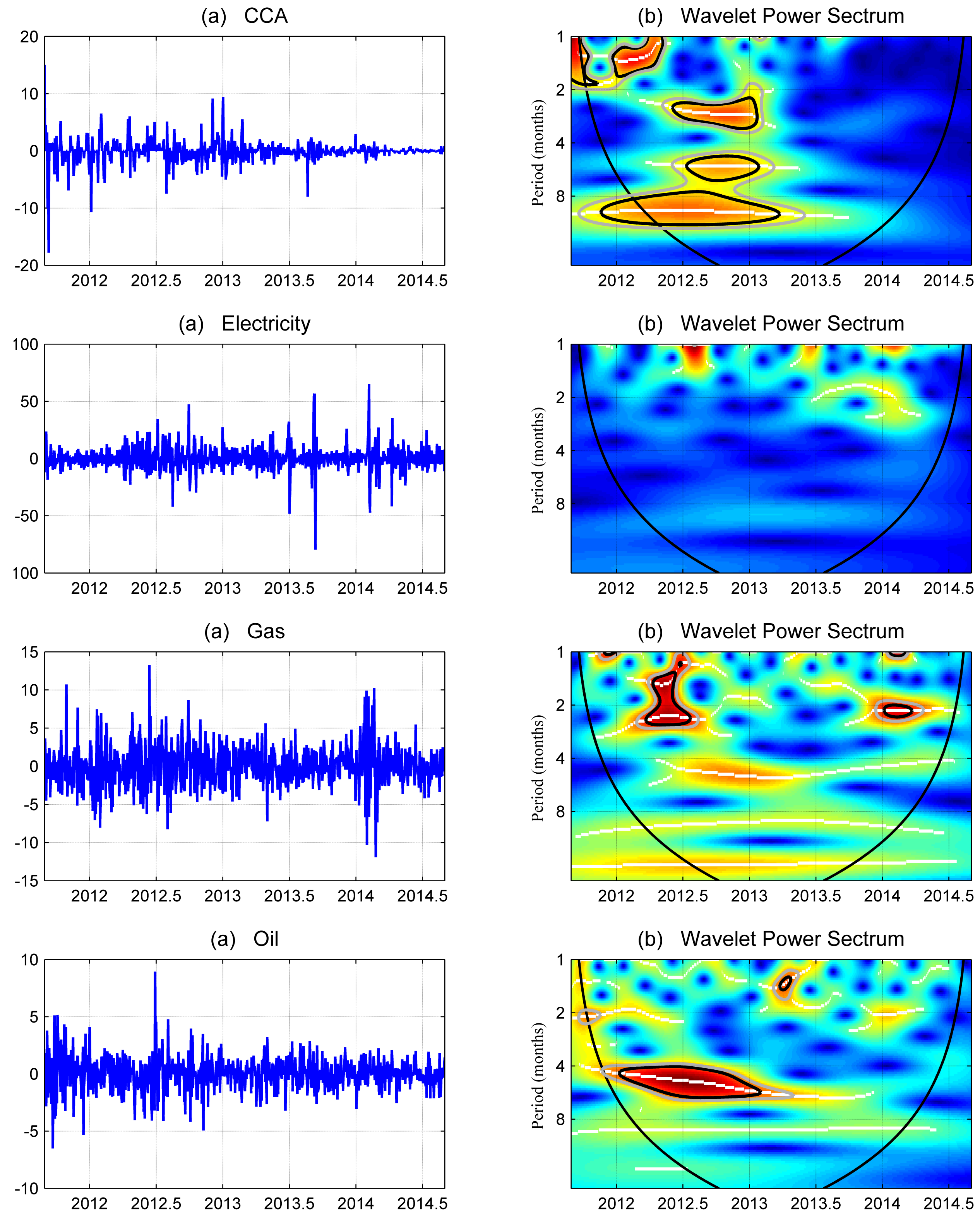

Figure 3: (a) Plot of the daily rate of return of each time-series. (b) The wavelet power spectrum. The black/gray contour designates the 5%/10% significance level. The cone-of-influence, which is the region affected by edge effects, is indicated with a black line. The color code for power ranges from blue (low power) to red (high power). The white lines show the maxima of the undulations of the wavelet power spectrum.

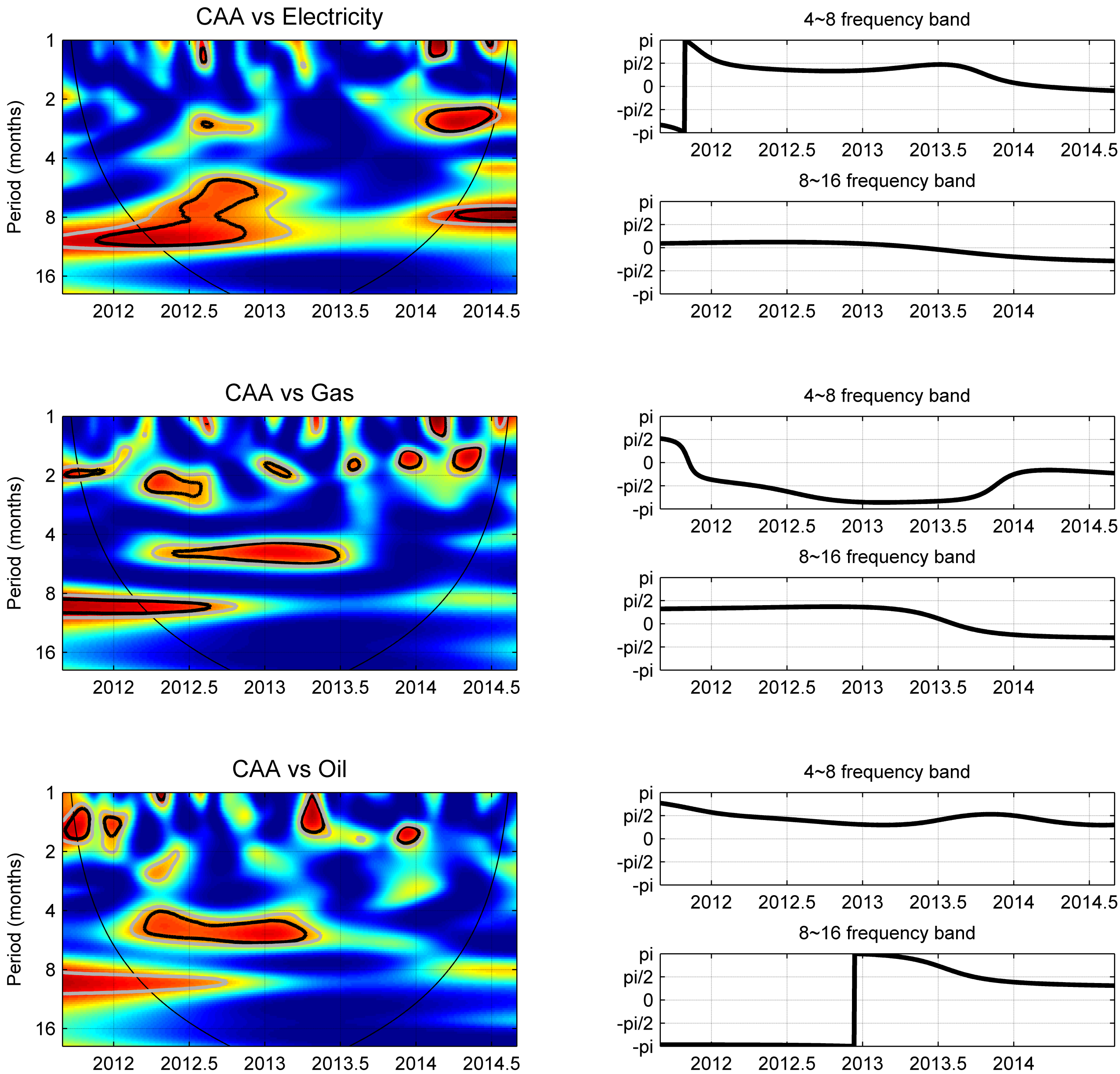

Figure 4: on the left — wavelet coherency. The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency — close to zero) to red (high coherency — close to one). On the right — partial phase-differences between CO2 and the other variable. Top: $2 \sim 8$ frequency band. Bottom: $8 \sim 20$ frequency band.

In Figure 4, we have the wavelet coherency between CO_2 and each of the other variables. Several conclusions can be drawn from these results. First, and perhaps surprisingly after Figure 3, there are large regions of high coherence. Between carbon and electricity prices, at low frequencies, corresponding to about one-year period cycles, coherence is statistically significant in the first half of the sample. For these frequencies, the phase-difference is essentially zero, showing that the two variables co-move together.

Between carbon and gas prices the relation is not stable across time and frequencies either. Until mid-2012, for frequencies corresponding to cycles of period eight or more months, coherence is statistically significant and the phase-difference, consistently between 0 and $\pi/2$, suggests that the variables are in-phase with the carbon prices leading. However, the picture changes somewhat when we look at higher frequencies, corresponding to period of four to six month cycles. For these frequencies, coherence is statistically significant from mid-2012 to mid-2013. The phase difference is consistently between $-\pi$ and $-\pi/2$, suggesting that variables are out-of-phase, with carbon still leading.

The pattern for the relation between oil and carbon is not homogeneous either. Again, we observe a statistically significant region until late 2012 for low frequencies, with the phase-difference being very close to $-\pi$, suggesting an almost perfect out-of-phase relation — at most with a slight lead for carbon prices. However, at higher frequencies, between four and six month period cycles, and running from early 2012 to early 2013, coherence is also statistically significant and the phase-difference is between 0 and $\pi/2$, telling us that the variables are in-phase, with carbon prices leading.

Finally, in Figure 5, we have the wavelet partial coherence between CO_2 and each variable, after controlling for the other variables. The results are now much cleaner, showing that the strongest relation is between electricity and carbon prices.

Focusing in frequencies associated with longer periods (eight months or more), carbon prices only reflect a strong coherence with respect to gas in the early part and late part of the sample, being strongly affect by the cone-of-influence. Therefore one should not infer too much from it. Still, it is interesting that the phase-difference is extremely consistent and very close to π, suggesting an almost perfect negative correlation. Focusing in shorter period cycles, around four months, there is an island of significant coherence between mid-2013 and mid-2014. For these frequencies and between these dates, the phase difference is between $-\pi$ and $-\pi/2$, showing a negative relation, with carbon prices leading.

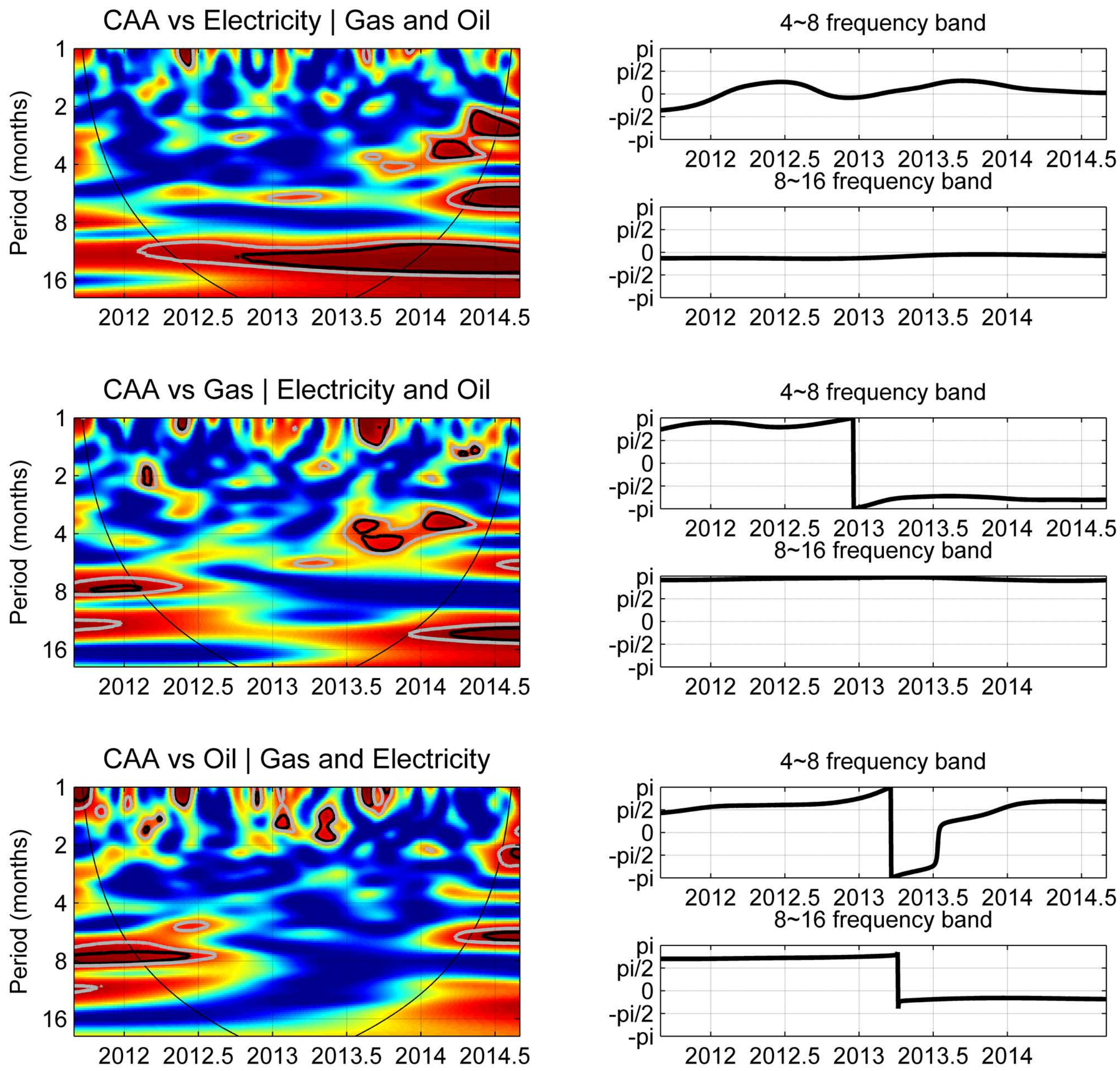

Figure 5: on the left — partial wavelet coherency. The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency — close to zero) to red (high coherency — close to one). On the right — partial phase-differences between CO2 and the other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

Regarding oil, the only statistical significant regions of high coherency are situated in the early part of the sample, until mid-2102, at a frequency corresponding to a eight-month period and in the late part, at a frequency of a six- month period. In both cases the phase-difference is consistently between $\pi/2$ and π, for such frequencies, showing that the variables are out-of-phase, with oil leading. Again, due the cone-of-influence, one should not pose too much attention to the results.

The most striking aspect of Figure 5 is the very strong and very stable relation (both with respect to coherency and phase-difference) between carbon and electricity prices, for frequencies of about one year period. The phase-difference is slightly negative until mid-2013 and essentially zero afterwards. This suggests that the variables are very tight in the longer run, co-moving together with, at most, a slight lead from electricity prices.

5 Concluding remarks and policy implications

In this paper, we presented a first analysis of the carbon prices in WCI, the emerging California emission market. After describing the market main features, we studied the interaction between carbon prices and energy prices, including oil, gas and electricity.

We applied multivariate wavelet analysis (MWA) tools with the purpose of analyzing the correlation between the various prices at different frequencies. Energy price dynamics is nonstationary, so it is important to use methods that do not require stationarity. MWA tools allow to go beyond the study of daily cycles that the VAR allows, using an adequate methodology, indicative of existent relationships in other, longer, cycles than daily. We note that changes in power supply quantities, on a large scale, are neither easy nor quick. So, it makes sense to consider the presence of long-term decisions, or at lower frequencies, i.e., correlations in longer temporal cycles. The results we obtain in MWA for lower frequencies are of particular relevance to market regulators, State governance and also emitting companies, because they provide a perception of the annual relationships between decision variables.

In a related study, Sousa et al. (2014) find that European carbon prices mostly reflect economic developments, and influence the price of final energy - electricity. In contrast, in California, we find the most important result in the relation between electricity prices and carbon, tight in the longer run, co-moving together with, at most, a slight lead from electricity prices. This result is in line with recent crediting of climate allowances in residential electricity bills. It regards the refunding of sold carbon allowances that were freely allocated in the beginning of the year, which the power generators did not use. It shows that the carbon price did not influence the price of electricity in California. The situation may be explained by the novelty of the market, but it may also be an indicator of an allowances surplus.

By the end of the first year of compliance (2013), there was an average of 1.8 MM weekly traded licenses, reaching 2.5 by the end of the year (The ICE, 2014[13]). This volume displays an increase in market liquidity. However, the fall in prices since the start of the year is another indicator of an allowances' surplus. Three aspects may be contributing to the surplus: first, the banking rules of AB32, allowed for future periods, though subject to some limits. Second, the growing renewable power production and increase in rain, in the Spring, fueling hydro power plants. Moreover, recently, fewer than expected emissions originating in Québec, recently linked to the California carbon market. These three reasons may cause the prices to remain near the bottom limit until 2020. The surplus problem has also been afflicting the European market, and California tried to prevent it by defining price control mechanisms. They include a price floor at auctions and a price containment reserve to 'slow down' peaks. Despite this potential problem, there has been a growth of sales of licenses for future years, conveying the idea that the WCI market will continue to operate, with credibility.

On natural gas, the main fossil fuel in the generating mix of California, our results show that carbon seemed to lead an out-of-phase relation in half-year cycles. However, this result is not as consistent as the electricity result, and we should not infer too much from it. Similarly, the EU result for natural gas also requires further investigation (Sousa et al. 2014).

Regarding the transport sector, with the inclusion of their distributors in the carbon market after 2015, consumers will be directly affected by greenhouse gas emissions limits in transport and home heating fuels. The causal out-of-phase link between CO_2 and oil, with oil leading, is already apparent in our study. We expect this relationship to intensify and gain significance when new phase data is included. Free allocation is not currently planned for fuels distributors, though one could argue that the licenses not used by the power utilities could be channeled to that sector. However, attending the possible situation of a licenses

[13] Carbon market North America available at https://www.pointcarbon.com/polopoly_fs/1.3478414!CMNA20131220.p

surplus, free allocation is an approach that may escalate the problem. An option should be to consider the use of personal climate revenues to accommodate the expected increase in gasoline and heating fuel prices. This solution would not tamper with the climate goal.

One should note some main structural differences between the EU ETS and WCI markets that should affect the variations in carbon prices, and in carbon price effects. In WCI, the inclusion of fuels distributors, the accounting of electricity imports per fuel, the existence of a price floor and ceiling, and the return to consumers of the selling value of free allocated licenses that have not been used. In EU ETS, the no-banking of licenses rule between periods. The WCI market features mean that the carbon price contains more information on GHG emitting activities and, more importantly, allows consumers of energy-intensive goods to be more aware of the cost of emissions.

In conclusion, we suggest that the first year and half of compliance of the WCI market advocates emissions' trading as a significant measure for climate change mitigation. The financial quantitative analytics we present here supports the development of the WCI in the post 2020.

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