A Wavelet Analysis of the Environmental Kuznets Curve in France

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Abstract

The paper explores the causality between carbon emission and economic growth in the case of France, for the period 1983Q2-2015Q2, by following a wavelet approach. The study offers detailed information of this nexus, for different frequencies and sub-periods of time, revealing the lead-lag nexus between variables under cyclical and anti-cyclical shocks. Different environmental-growth hypotheses are found in the case of France, for a given period of investigation, which varie from sub-periods to sub-periods, from short to medium and long terms, under particular national and international economic contexts.

Keywords: Carbon emissions, Growth, Effects, Wavelet analysis

1. Introduction

Over the last decades, the environmental degradation became one of the most investigated phenomenon on the literature in the field. As this issue is indissoluble related to the economic growth, the impact of growth on environmental degradation started to arise a special interest for researchers. They intensified the forces to understand the complexity of generated negative effects and to find the needed adjustments to deal with. The partisans of this hypothesis emphasize that the environmental pollution increases in tandem with the economic growth, reaches a peak as maximum level, and after that falls. This curve is called the Environmental Kuznets Curve (EKC). At the first stage of industrialization, the people give an accentuated importance to the economic growth, neglecting the aspects related to the environmental degradation. Further, as the standard of living increases, the people move their attention from welfare standard to environmental comfort, trying to better control the pollution.

On this ground, this investigation explores the link between carbon dioxide (CO_2) and economic growth in the case of France, for the period 1983Q2-2015Q2. The main used tool is wavelet.

France arises a special interest, as this country extensively followed complex policies for environmental protection over the last decades. One of the first set of such policies was taken during the decentralization process from '80. The decentralization reform from 1982 brought, starting with 1992, the 'Directions Regionales de l'Environnement' (DIREN), establishments in charge with the environmental policies at regional levels. Separately, France became part of many commitments under the aegis of different international conventions and protocols regarding the control of atmospheric pollution and climate change. France ratified the United Nations Framework Convention on Climate Change in March 1994, which has been extended through the Kyoto Protocol in 1997. The main aim of these commitments is the stabilization of CO_2 emissions between 1990 and 2008-2012 average (e.g. France reduces the emission on this period with 9.6%). Under European Commission, France is partner of the Climate and Renewable Energy Package, which has as target the reduction of greenhouse gas emissions and establishing CO_2 emission standards for new passenger cars. The set of document came into force on June 2009. France firmed also the Transboundary Air Pollution document, known as the Geneva Convention, on November 1979, coming into force on January 1998. Several protocols completed the main document: the Gothenburg Protocol, in July 2003 (i.e. for pollutants involved in acidification, eutrophication and photochemical pollution), and the two Aarhus Protocols, in July 2002 and July 2003 (i.e. the first one concerns the heavy metals, while the second one is related to the persistent organic pollutants-POPs). Several other protocols were firmed by France: the Helsinki Protocol on sulfur dioxide (SO_2) reduction in March 1986, the Sofia Protocol on nitrogen oxides (NO_x) reduction in July 1989, the Geneva Protocol on non-methane volatile organic compounds (NMVOC) reduction in June 1997, and the Oslo Protocol also on SO_2 gradual reduction in August 1998.

Thus, France exhibited during the period 1983-2015 a continuous and an accentuated decrease in the level of carbon emissions, from 1.81 tonnes per capita in 1983Q1 to 1.44 tonnes per capita in 2015Q2, the reduction being of 20.44%. Over this period, the gross domestic product (GDP) per capita tripled, from 3,200.8 US PPP[1] dollars in 1983Q1 to 9,900.8 US PPP dollars in 2015Q2. France is also one of the largest nuclear power in the world in respect to the electricity produced with nuclear power plants, with 74.3% of total electricity produced in 2013[2]. All these aspects reinforce the France's care for the reduction of carbon emissions. On this ground, the widespread use of nuclear energy pollutes less, offering a strong base for the 'good part' of EKC in France, when the economic growth attenuates the carbon emissions.

The paper offers many novelties for the literature in the field. Evidences for the first time, at our knowledge, in the case of France, how the connection between carbon emissions and growth varies across different frequencies and different period of time (i.e. the study presents a general framework of environment-growth policy in France, on short-, medium- and long-runs). Secondly, it is one of the first papers from the literature which uses the wavelet tool for investigations in the environment-growth area, by focusing on the EKC in France. We note that this approach offers new insights compared to classical ones, as it describes how the variables interact at different frequencies and how they evolve over time. Thirdly, the analysis shows detailed information regarding the status of carbon emission-growth nexus, for both causality and signs of variables, from cyclical and anti-cyclical point of view.

The paper is organized as follows. Section 2 presents a literature review. Section 3 describes the data and methodology, while Section 4 presents the empirical results. Finally, Section 5 offers some concluding remarks.

2. Literature

There are many papers which investigate the relationship between environmental degradation and economic growth. Having as starting point the EKC, the partisans of this research area tried to demonstrate empirically this hypothesis, by following different countries and periods, various dataset and methodologies, with different outputs.

The literature focused on environmental degradation-growth pair can be divided by using two criteria: the type of assumed function and the number of targeted countries. Based on the first criterion, the assumption goes from

[1]US PPP denotes the United States Dollars in Purchasing Power Parities.
[2]World Bank, World Development Indicators on-line database (2016).

linear to non-linear function, while according on the second one, the analyses vary from models with one country to models with more than one country.

Related to the type of assumed function, the literature in the field widely explores different sorts of relationship between environmental degradation and economic growth, especially based on empirical approaches. Holtz-Eakin and Selden (1995); Halicioglu (2009); Kohler (2013) and Yavuz (2014) claim the quadratic connection between pollution and income, by inverted U-shape. This group reinforces the non-linear assumption and shows that there is a given level of pollution for that the growth is maximum. Other researchers, such as Moomaw and Unruh (1997); Galeotti et al. (2006) or Wang et al. (2011), test the superior polynomial order of assumed function (i.e. more than 2) and put in evidence the cubic relationships, with N-shape. Obtaining more complex findings, Yang et al. (2015) demonstrate, for 67 countries, different non-linear types of functions, from inverted U- to inverted N-shape and M-shape. Alkhathlan and Javid (2013) investigates the case of Saudi Arabia, by following monotonically increasing models. The main finding show that the income per capita rises when the pollution increases. They also find that the electricity consumption is less polluting than the oil and gas consumptions. Separately, there also are researchers who have serious reserves regarding the existence of EKC (Agras and Chapman, 1999; Richmond and Kaufmann, 2006), their empirical outputs not validating it.

The second criterion uses for the literature review allows us to identify papers which analysis one country and papers which have as target more than one country. The first group of papers considers time series data, while the second one includes cross-sectional or panel samples.

The papers which explore only one country follows various period of times, have as target countries from different continents and/or regions and reveals various findings. Many studies are included in this category. For example, Akbostanci et al. (2009) and Halicioglu (2009) select the Turkey for their investigations, for the period 1968-2003 and 1960-2005, respectively. If the first paper evidences a monotonically increasing function between carbon dioxide and economic growth on long-run, the second one reinforces the EKC hypothesis. Lau et al. (2014) chooses the Malaysia for their research, but follow different period of time. The study covers the years 1970-2008 and validates the EKC on short- and long-run, but only after the control with foreign direct investments (FDI) and trade. Monotonically increasing of economic growth to pollution also find Lim (1997) for South Korea, Kunnas and Myllyntaus (2007) in the case of Finland, Miah et al. (2010) for Bangladesh, and Alkhathlan and Javid (2013) for Saudi Arabia. EKC is validated by Kristrom and Lundgren (2005) in the case of Sweden, Nasir and Rehman (2011) for India, and Jayanthakumaran et al. (2012) in the case of China and India. N-shaped function is found in Austria by Friedl and Getzner (2003).

The second set of papers includes more than one country, uses cross-sectional or panel samples and offers a diversity of outputs, France being subject of investigation by many of them. Monotonically increasing hypothesis is revealed for different periods of time by Richmond and Kaufmann (2006); Azomahou et al. (2006); and Iwata et al. (2011), for various group of countries, including the Organization for Economic Cooperation and Development (OECD). By following non-linear approach, EKC is validated for the OECD by Dijkgraaf and Vollebergh (2001); Han and Lee (2013), and Cho and Li (2014). N-shaped function is demonstrated by Moomaw and Unruh (1997) and Martinez-Zarzoso and Bengochea-Morancho (2004) for the same group of countries. Curiously, Galeotti et al. (2006), exploring also the OECD area, obtain an inverted N-shaped connection.

Only two papers on the topic of CO2 emissions-growth are exclusively devoted to the case of France. The first paper belongs to Ang (2007), covers the period 1960-2000 and uses as variables CO2 emission, commercial energy use, and per capita real gross domestic product (GDP). The author chooses a battery of tools, comprising the Granger causality, Vector Error Correction (VEC) and Autoregressive Distributed Lag (ARDL) estimations. The main findings show that between CO2 and pe capita GDP there is a quadratic relationship, validating the EKC hypothesis on long run. Aside from this, also on long run, the Granger causality analysis reveals the growth explains CO2 emission and energy consumption, but with unidirectional direction. Interesting, Ang (2007) intuitively recognizes, but does not demonstrate, the existence of the reverse causality, which runs from CO2 emissions to GDP. He argues that such connection claims for environmental protection as the pollution can generate negative externalities (i.e. worsens the human health and reduces the economic productivity).

A new research regarding France performs Iwata et al. (2010). They covers the period 1960-2003 and follow quasi the same tools used by Ang (2007), but introduces in the pollution-growth equation a new variable - the nuclear energy. The EKC is also confirmed and presents stability over time. The Granger causality shows a one-way causality between CO2 and GDP growth, which runs from GDP growth to CO2. We underline herein that both papers do not claim any validation of the Granger causality on the opposite way, which drives from CO2 emissions to GDP growth.

This diversity of results is the vector of several reasons, as Yang et al. (2015) and Hill and Magnani (2002) note. Firstly, the investigators follow different proxy to capture environmental variables, from monoxide of carbon (CO) and dioxide of carbon (CO2) to sulphur dioxide (SO2), sulphur oxide (SOx) or volatile organic compounds (VOC). The second reason is related to the data-set used, being registered different periods of time and various category of samples, from time-series to cross-sectional or panel types. Thirdly, the findings are generated by applied different empirical tools. There are notable here ARDL models (Jayanthakumaran et al., 2012; Kohler, 2013), Johansen co-integration approach (Nasir and Rehman, 2011), decomposition analysis (Lise, 2006), disaggregate estimations (Alkhathlan and Javid, 2013), pooled models (Martinez-Zarzoso and Bengochea-Morancho, 2004; Iwata et al., 2011), Generalized Method of Moments (GMM) (Han and Lee, 2013), non-parametric panel estimations (Azomahou et al., 2006) and dynamic models (Lee et al., 2009).

Additionally, many authors started to develop the literature in the field by including other different determinants on the environmental degradation - growth pair: the financial development (Tamazian et al., 2009; Sedorsky, 2010; Tamazian and Rao, 2010; Jalil and Feridum, 2011), the energy consumption (Paul and Bhattacharya, 2004; Richmond and Kaufmann, 2006; Soytas et al., 2007; Luzzati and Orsini, 2009; Halicioglu, 2009; Apergis and Payne, 2010; Wang et al., 2011; Farhani and Rejeb, 2012; Shahbaz et al., 2013), the trade (Palamalai et al., 2015; Sebri and Ben-Salha, 2014) or the oil consumption (Al-Mulali, 2011).

Overall, the present paper explores the carbon emissions-growth nexus under an extended literature, with a variety of approaches, as Kijima et al. (2010) observe: static vs. dynamic, microeconomic vs. macroeconomic, short vs. long term, stochastic vs. deterministic. Between them, wavelet arises a special interest over the last decades. Developed by Morlet and Grossmann in the early 1980s, this tool was extensively used in various fields, from geophysics and image processing to medicine and astronomy. More recent, the wavelet started to win many adepts also in economics area.

3. Data and methodology

Two variables are selected in order to investigate the connection between carbon emissions and economic growth in the case of France: the carbon emissions and the GDP per capita, denoted by x and y, respectively. The carbon emissions *(y)* describes the volume of carbon emissions expressed in tonnes per capita. Generally, the literature offers support for CO2, SO2 or NOx (e.g. de Bruyn et al., 1998) as main measures of environmental degradation, but these indicators are not available with infra-annual frequencies and/or for a long period of time. The GDP per capita *(x)* is widely used in the environmental-growth literature to capture the economic growth, even if for other authors this index denotes the essence of economic development (see Grossman and Krueger, 1991, 1995; Cypher, 2014). The indicator shows the volume of GDP per capita and is expressed in US dollars in Purchasing Power Parities (PPP).

As novelty for the empirical literature in the field, both variables have quarterly frequencies and cover the period 1983Q2-2015Q2. Their source of data is the Oxford Economics database (2015). We use in our study only two variables as the wavelet is a bivariate tool. Beside of this, comparing to the existing literature which consider various control determinants (i.e. energy consumption, electricity production from nuclear source), our two variables express the carbon emissions-growth link only, without being interested in the analyse of the sources of pollution. Not at least, the availability in France of longer datasets in environmental degradation and energy area with infra-annual frequency is limited to the carbon monoxide.

The first step in the analysis of time series with infra-annual frequencies (i.e. quarterly, in our case) is to deal with any seasonal components. Hence, Census X12 methodology is used to adjust both series for seasonal components, while the final working series appear in natural logarithm form. Further, as the stationarity is required propriety for analysis in time-series domain, several unit root tests are employed: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS).

According to Dar et al. (2014), the "true economic relationship among variables can be expected to hold at disaggregated (scale) level rather than at the usual aggregation level"(p.3). As consequence, in order to explore the connection between environmental degradation and economic growth in the case of France, we deal with these issues by following a bivariate wavelet approach, with the carbon emission and GDP per capita as main variables, in natural logarithm forms, after the unit root checks. This tool is also required by the particularities of environmental-growth policies, which operates with different horizon of times, from short- to medium- and long-terms.

The wavelet tool is superior to the classical ones by many aspects. Concretely, the wavelet offers several advantages: (1) depicts short, medium and long-run frameworks, (2) evidences any non-linearity of the function, (3) describes how the connection between variables varies across different frequencies and different period of times, (4) shows the direction of causality at different frequencies over time, and (5) highlights the lead-lag status of the nexus (i.e. cyclical or counter-cyclical status).

Time and frequency are the main characteristics of the wavelet, which is a function with zero mean. There are various types of wavelets, each one with complex features, the literature in the field being prolific in this way (e.g. Morlet, Mexican hat, Haar or Daubechies). As the wavelet coefficients $W_X(s,\tau)$ contain mixed information about the function *x(t)* and the considered wavelet, it is crucial the selection of the function, which depends by the targeted application. Herein, t illustrates the time, s denotes a scaling or dilatation factor which controls the length of the wavelet, while τ indicates where the wavelet is centred, revealing a location parameter.

The wavelet amplitude and phase are two aspects essential for the studies of the business cycle synchronism between different economic variables. We choose the Morlet wavelet type, as this function seems to fit better our needs because it is a complex one and facilitates to receive important informations regarding both amplitude and phase.

The Morlet function, in a simplified version, is presented us follows:

$$\psi_\eta(t) = \pi^{-1/4} e^{i\eta t} e^{(-1/2)t^2}, \quad (1)$$

where η captures the central frequency, while i represents $\sqrt{-1}$. The central frequency is six ($\eta = 6$), as this level of frequency (f) offers a good balance between time and frequency localisation. The wavelet scale is inversely related to the frequency (i.e. $s=1/f$).

Two main classes of wavelet transformation can be identified: the discrete wavelet transformation (DWT) and the continuous wavelet transformation (CWT). As Tiwari et al. (2013) emphasise, if the first type of wavelet generally fits the noise reduction and data compression, the second one offers better results for feature-extraction purposes and represents the right choice for our approach. Related to the 'morlet wavelet' (ψ), as function of $W_X(s,\tau)$, the

CWT is:

$$W_X(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\psi^*\Big(\frac{t-\tau}{s}\Big)dt, \tag{2}$$

where * is the complex conjugate form.

On this ground, the CWT transformation of a discrete time series $\{x_n\}$, with $\{x_n,\ n=0,\ \ldots,\ N\text{-}1\}$ of N observations and uniform time step δt, has this form:

$$W_m^X(s) = \frac{\delta t}{\sqrt{s}} \sum_{n'=0}^{N-1} x_{n'}\psi^*\Big((n-m)\frac{\delta t}{s}\Big), \tag{3}$$

with *m=0,1...N-1*.

Torrence and Compo (1998) propose several sequences in order to apply the CWT routine, which generates: the wavelet power spectrum, the cross-wavelet power, the wavelet coherency and the phase difference.

3.1. Wavelet power spectrum

As local variance, the wavelet power spectrum is defined as $|W_n^X|^2$. Herein, the cone of influence depicts the edge effects of the observations, below it the observations being impacted with the edge effects. The statistical significance of wavelet power is tested through a null hypothesis, while a stationary process with a certain background power spectrum P_f represents the starting point of data generating process.

Torrence and Compo (1998) consider white (with a flat Fourier spectrum) and red noise (increasing power with decreasing frequency) for the wavelet power spectra. Under the null hypothesis, the distribution for the local wavelet power spectrum has this form:

$$D\bigg(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p\bigg) = \frac{1}{2}P_f\chi_v^2, \tag{4}$$

for time n and scale s. The mean spectrum at the Fourier frequency f is P_f, being connected with the wavelet scale s (i.e. $s \approx 1/f$). The σ denotes the variance, whereas the v is equal to 1 for real wavelet or 2 for complex wavelet. The general processes are employed relied on the Monte-Carlo simulations.

3.2. Cross-wavelet power

The cross-wavelet power (XWT) has its origins on the seminal work of Hudgins et al. (1993). XWT of two time series, x=$\{x_n\}$ and y=$\{y_n\}$, has this form:

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s). \tag{5}$$

In this case, W_n^X and W_n^Y are the wavelet transforms of x and y, while the cross-wavelet power is $|W_n^{XY}|$. Subsequently, the confined covariance between variables is given by the cross-wavelet power spectrum at each scale or frequency and has background on the Fourier power spectra P_k^X and P_k^Y.

Torrence and Compo (1998) also offer the theoretical distribution of cross-wavelet power, which can be write as follows:

$$D\left(\frac{|W_X(s)W_Y^*(s)|}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y}, \tag{6}$$

where, for a *pdf* (probability of density function) as the square root of the product of two χ^2 distributions, the confidence level associated with the probability p is $Z_v(p)$.

3.3. Wavelet coherency

The wavelet coherency (WTC) is defined by Aguiar-Conraria et al. (2008) as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series"(p.2872).

WTC has this form:

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|}{S(s^{-1}|W_n^X(s)|)^{1/2} S(s^{-1}|W_n^Y(s)|)^{1/2}}, \tag{7}$$

where S represents a smoothing operator in both time and scale.

3.4. Phase difference

Based on Aguiar-Conraria et al. (2008), the phase ϕ_x of time series x=$\{x_n\}$ should be treated as the position in the pseudo-cycle of the series. The mean and confidence interval of phase difference determines the phase difference ϕ_{xy} of two time series.

The ϕ_{xy} is as follows:

$$\phi_{x,y} = tan^{-1}\left(\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}\right). \tag{8}$$

When the phase difference is zero, the time series move together at the specified frequency. When $\phi_{xy} \in [0, \frac{\pi}{2}]$, the series are in phase and y leads x, and when $\phi_{xy} \in [\frac{-\pi}{2}, 0]$, the series still are in phase but x leads y. Conversely, when the phase difference is π or $-\pi$, the series are out of phase. In this case, x leads y when $\phi_{xy} \in [\frac{\pi}{2}, \pi]$, while y leads x, for $\phi_{xy} \in [-\pi, \frac{-\pi}{2}]$.

4. Data analysis and findings

The descriptive statistics and box-plot of GDP per capita *(x)* and carbon emissions *(y)*, in natural logarithm form, with quarterly frequency, for the period 1983m2-2015m2, are presented in Appendix (Table A1 and Figure A1). In order to check the stationarity of the time series, the ADF, PP and KPSS tests are performed. The tests are employed in level and first-difference, with intercept, and also with trend and intercept, respectively. The results are reported in the Table 1.

Table 1: The unit root tests of ln GDP per capita *(x)* and carbon emissions *(y)*

Test		Variables			
		Ln(x)	Ln(y)	d(ln(x))	d(ln(y))
ADF	Intercept	-3.107*	0.636	-3.483**	-16.719***
	Trend and intercept	-0.494	0.497	-4.729***	-16.648***
PP	Intercept	-3.330**	0.481	-2.858*	-19.420***
	Trend and intercept	-0.517	0.053**	-3.220*	-19.929***
KPSS	Intercept	1.382	0.837	0.667*	0.206***
	Trend and intercept	0.295	0.251	0.042***	0.127**

Notes: ***, **, and * denote the significance at 1, 5 and 10% level of significance, respectively.

All three tests (i.e. ADF, PP and KPSS) validate that both variables are non-stationary in level and stationary in the first-difference, at 1 and 5% levels of significance. As consequence, for the further steps of the investigation, the variables are used in their first-difference, becoming *d(ln(x))* and *d(ln(y))*, respectively.

The CWT power spectra[3], defined in equation (4), of the *d(ln(x))* and *d(ln(y))*, in the case of France, with quarterly frequency, are presented in Figures 1 and 2 below.

Figure 1 shows that the wavelet power of *d(ln(x))* is high and significant for medium frequency (i.e. medium term), at 4-16 quarters of scale (band), but only for the period 2003-2015. The series intensively registers high power for low frequency (i.e. long term), which corresponds to 16-33 quarters of scale (band), for quasi-all period of time. Differently, *d(ln(y))* presents high power only for high and medium frequencies (i.e. short and medium terms), up to 6-7 quarters of scale (band), for whole analysed period, as Figure 2 shows. By comparing the two spectra, it is clear that some common power features of the series are registered only on high frequency (i.e. short term), for 4-7 quarters of scale, for the period 2009Q2-2011Q4.

These common features might be the result of a simply coincidence. Thus, additional information about the co-movement between *d(ln(x))* and *d(ln(y))* offers the cross-wavelet power, as Figure 3 plots.

The XWT of the pair *d(ln(x))-d(ln(y))* plots three zones of interest. The first zone corresponds to powerful and significant relationships between variables at medium frequency, (i.e. medium term), for 5-6 quarters of scale, and two sub-periods: 2003Q3-2004Q1 and 2009Q2-2011Q4. As the frequency increases, but remaining on the same medium frequency, the second zone appears between 7 and 15 quarters of scale. Here, the connection between variables has the same intensity and covers the period 2011Q4-2015Q2. The third zone registers a low intensity of interaction between variables and covers the period 1986Q4-1998Q1, at low frequency (i.e. long term), for 20-33 quarters of scale. For all zones, the variables are in phase and have each other cyclical effect, excepting the end of the period, for 7 to 15 quarters of scale, when the effect changes to anti-cyclical one.

Unfortunately, such a XWT approach has many critics, as it do not take into account the normalization to the wavelet power spectrum. Without normalization, the XWT can produce misleading outputs when one spectra is locally and the another one presents peaks (i.e. the peaks generate spurious correlation between variables which actually are not correlated). As the XWT fails to depict the right connection between two variables, a new

[3]For all wavelet estimations, we used the R-codes proposed by Roschand and Schmidbauer (2014), in "WaveletComp: A guide tour through the R-package".

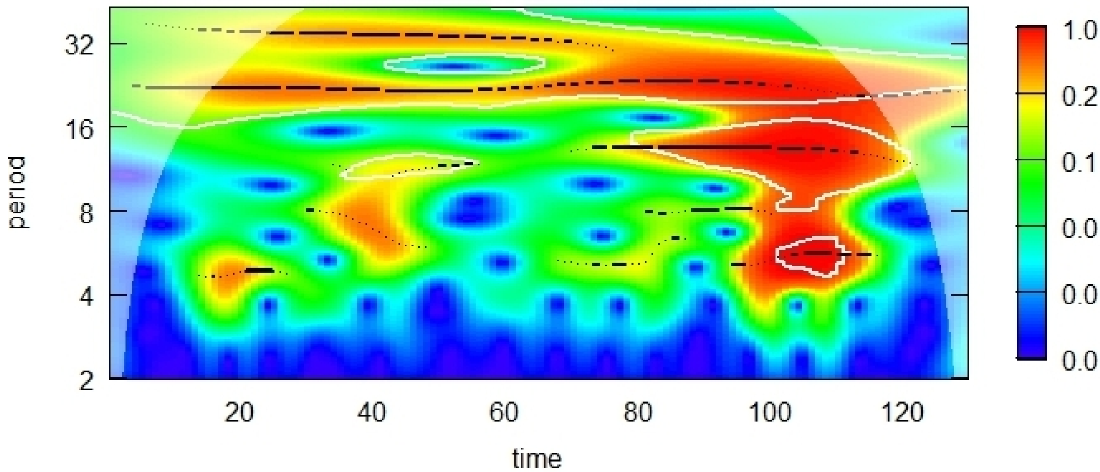

Figure 1: CWT power spectrum of d(ln(x)) - GDP per capita, quarterly frequency

Note: (1) The cone of influence (COI) where the edge effects might distort the picture is presented as a lighted shadow, while the thick white contour denotes the 5% significance level against red noise;
(2) The colour code for power ranges goes from blue (low power) to red (high power);
(3) The X-axis represents the analysed time period, and the Y-axis reveals the frequency.
(4) On the X-axis, the time 20 corresponds to 1988Q1, 40 to 1993Q1, 60 to 1998Q1, 80 to 2003Q1, 100 to 2008Q1, and 120 to 2013Q1, respectively.

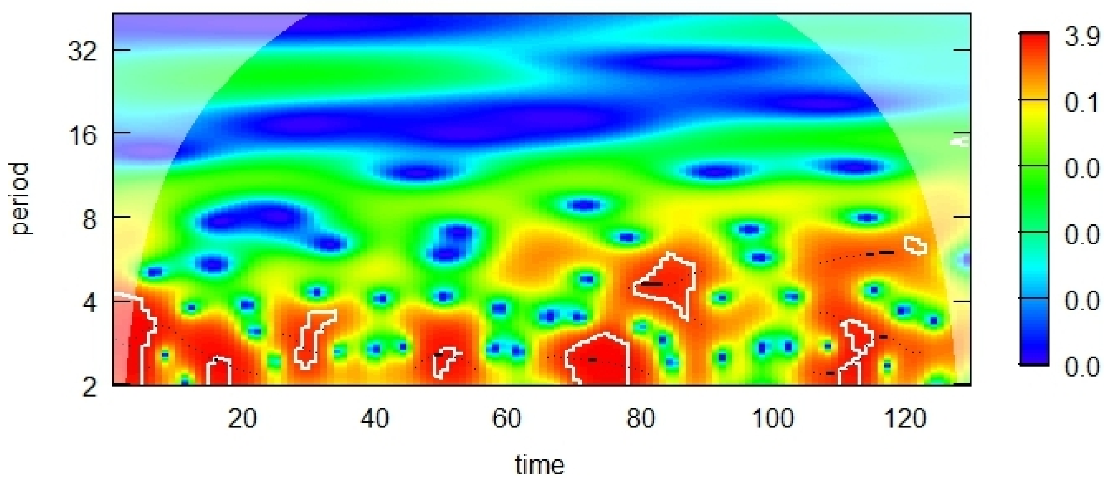

Figure 2: CWT power spectrum of d(ln(y)) - carbon emission, quarterly frequency

Note: (1) The cone of influence (COI) where the edge effects might distort the picture is presented as a lighted shadow, while the thick white contour denotes the 5% significance level against red noise;
(2) The colour code for power ranges goes from blue (low power) to red (high power);
(3) The X-axis represents the analysed time period, and the Y-axis reveals the frequency.
(4) On the X-axis, the time 20 corresponds to 1988Q1, 40 to 1993Q1, 60 to 1998Q1, 80 to 2003Q1, 100 to 2008Q1, and 120 to 2013Q1, respectively.

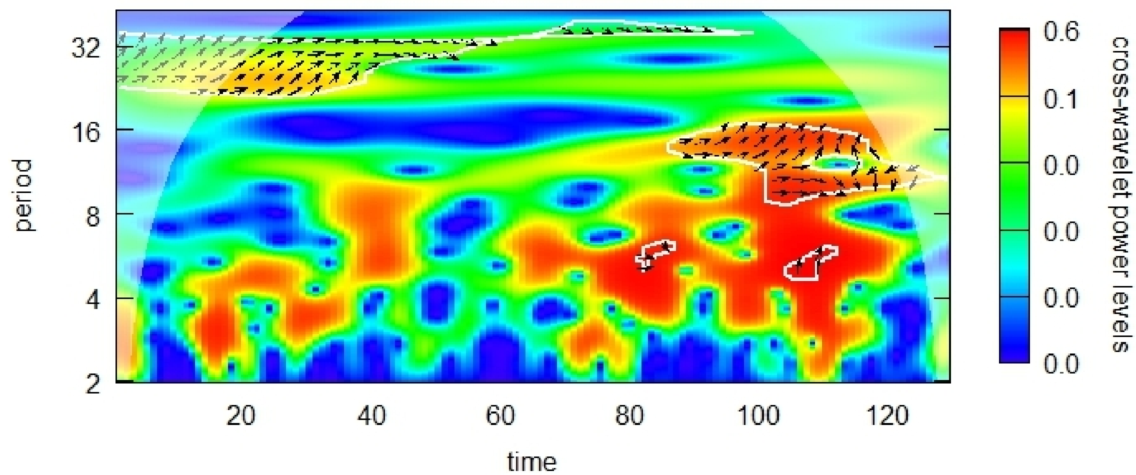

Figure 3: XWT of the pair d(ln(x))-d(ln(y)), quarterly frequency

Note: (1) The the cone of influence (COI) where the edge effects might distort the picture is designed as a lighted shadow, while the thick white contour depicts the 5% significance level estimated from Monte Carlo simulations by following phase randomized surrogate series;
(2) The colour code for power ranges goes from blue (low power) to red colour (high power);
(3) The arrows illustrate the phase difference between the two series. The variables are in phase when the arrows are oriented to the right (positively related). In phase, the GDP per capita is leading when the arrows are oriented to the right and up, while the carbon emission is leading when the arrows are oriented to the right and down.
(4) The variables are out of phase when the arrows are pointed to the left (negatively related). The carbon emission is leading when the arrows are pointed to the left and up, while the GDP per capita is leading when the arrows are oriented to the left and down.
(5) In phase, the variables have each other cyclical effect and in out of phase, an anti-cyclical one.
(6) The X-axis illustrates the analysed time-period, whereas the Y-axis shows the frequency.
(7) On the X-axis, the time 20 corresponds to 1988Q1, 40 to 1993Q1, 60 to 1998Q1, 80 to 2003Q1, 100 to 2008Q1, and 120 to 2013Q1, respectively.

superior wavelet power tool is required: the WTC.

The WTC of the pair *d(ln(x))-d(ln(y))* is plotted in Figure 4 and shows, both in frequency and time, how are correlated the two variables. Figure 4 yields various and interesting situations.

The main important findings partially validate the EKC in France, for both low and medium frequencies, but for different sub-periods of time, as GDP per capita causes carbon emissions. The 'good part' of EKC is found at medium frequency, for 3-12 quarters of scale (i.e. medium term), for the sub-periods 1990Q3-1994Q1 and 1998Q3-2000Q3. In this case, as the arrows are pointed to left and down, the GDP per capita is negatively correlated with the carbon emissions, the variables being out of phase. The 'bad part' of EKC is also proofed. Herein, the arrows are oriented to right and up,

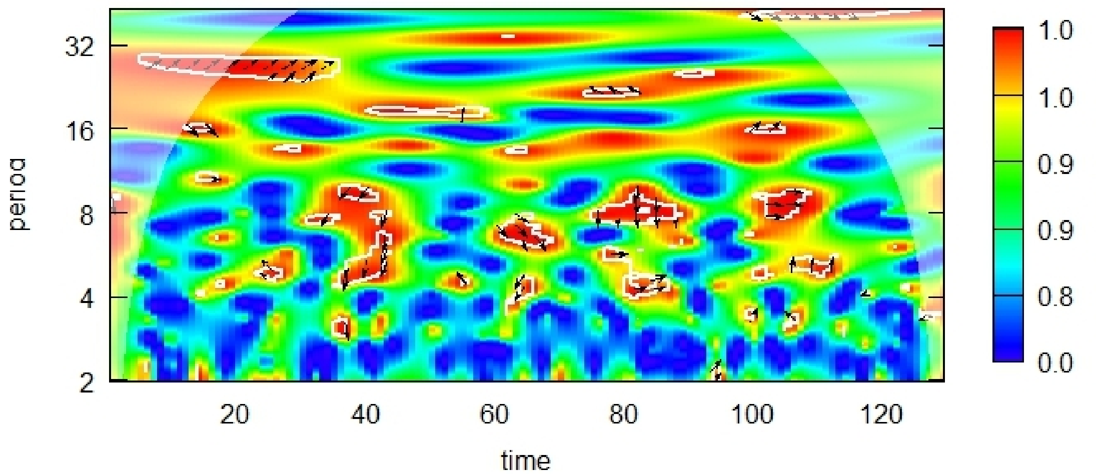

Figure 4: WTC of the pair d(ln(x))-d(ln(y)), quarterly frequency

Note: (1) The the cone of influence (COI) where the edge effects might distort the picture is designed as a lighted shadow, while the thick white contour depicts the 5% significance level estimated from Monte Carlo simulations by following phase randomized surrogate series;
(2) The colour code for power ranges goes from blue (low power) to red colour (high power);
(3) The arrows illustrate the phase difference between the two series. The variables are in phase when the arrows are oriented to the right (positively related). In phase, the GDP per capita is leading when the arrows are oriented to the right and up, while the carbon emission is leading when the arrows are oriented to the right and down.
(4) The variables are out of phase when the arrows are pointed to the left (negatively related). The carbon emission is leading when the arrows are pointed to the left and up, while the GDP per capita is leading when the arrows are oriented to the left and down.
(5) In phase, the variables have each other cyclical effect and in out of phase, an anti-cyclical one.
(6) The X-axis illustrates the analysed time-period, whereas the Y-axis shows the frequency.
(7) On the X-axis, the time 20 corresponds to 1988Q1, 40 to 1993Q1, 60 to 1998Q1, 80 to 2003Q1, 100 to 2008Q1, and 120 to 2013Q1, respectively.

meaning that between variables are cyclical effects. The GDP per capita drives carbon emissions, with the same sign. Such effects are registered at medium frequency, which corresponds to 3-12 quarters of scale (i.e. medium term), for the sub-periods 2002Q3-2005Q1 and 2008Q3-2011Q4, and at low frequency, related to 12-32 quarters of scale (i.e. long term), for the sub-periods 1985Q3-1992Q3 and 2008Q3-2009Q4.

Conversely, the results evidence few situations of reverse causality, when the carbon emissions cause GDP per capita. Carbon emissions positively influence GDP per capita at medium frequency, for the sub-period 1998Q3-2000Q4, which corresponds to 3-12 quarters of scale (i.e. medium term). The same positive impact is also registered at low frequency, for 1985Q3-1992Q3, with 12-32 quarters of scale (i.e. long term). In only one case the variables are out of phase, when the carbon emissions have negative influence on GDP per capita. This connection characterises, at low frequency, the sub-period 2002Q3-2003Q4 and corresponds to 12-32 quarters of scale (i.e. long term).

Interesting, no EKC is proofed at very high frequency. More precisely, up to 3 quarters of scale (i.e. short term), there is no causality between carbon emissions and GDP per capita.

The findings offer support for several environmental degradation-growth hypotheses (e.g. Holtz-Eakin and Selden, 1995; Agras and Chapman, 1999; Richmond and Kaufmann, 2006; Ang, 2007; Halicioglu, 2009; Iwata et al., 2010; Kohler, 2013; Alkhathlan and Javid, 2013; Yavuz, 2014), but only partially, more precisely, for specific sub-periods of time. We do not confirm the findings which claim the evidence of a non-linear connection between pollution and growth, with polynomial order more than 2 (e.g. Moomaw and Unruh, 1997; Galeotti et al., 2006; Wang et al., 2011; Yang et al., 2015). The differences arise especially from the used tool, analysed period and followed data frequency.

By applying wavelet method, our new results unravel the time and frequency dependencies between carbon emission and GDP per capita, in the case of France, which could not be detectable through the classical econometric tools.

5. Conclusions

The study explores the causality between the carbon emissions and GDP per capita, in the case of France, for the period 1983Q2-2015Q2, by following the wavelet approach. The analysis emphasises detailed information about this nexus, for different sub-periods of time and frequencies, highlighting the lead-lag status between variables under the impact of cyclical and anti-cyclical shocks.

In France, the EKC is not validated on short term, meaning that does not exist any influence of GDP per capita on carbon emissions. The foundation of environmental regional agencies in the late '80 and the effects of Kyoto protocol from 1997 seem to improve the environmental status, as the increase of GDP per capita reduced the carbon emissions, but only on medium term. This 'good' part of EKC is the results of much more attention given to the pollution. After 2002, the rest of commitments followed by France (i.e. Aarhus Protocols from 2002 and 2003, Gothenburg Protocol from 2003 and Climate and Renewable Energy Package from 2009) did not have the same positive effects on medium term, the accent being exclusively put on the economic growth. Moreover, the world economic crisis transformed the growth in one of the first desideratum for the French government, neglecting the environmental policies. Here, the 'bad' part of EKC is registered. Unfortunately, for a short period of time, the pollution seemed to drive growth, but in this case other determinants of growth have much more importance than pollution. The investments can play a key rule in this case as the positive effects on growth of investment multiplier are less than the negative ones generated by pollution (i.e. the investment generates growth but pollutes more).

Until 1992, on long term, after the Helsinki Protocol from 1986, pollution positively generates growth, followed by 'bad' EKC part. For a short period (i.e. 2002-2003), on the ground of Aarhus and Gothenburg Protocols (2002 and 2003), any increase of carbon emissions inhibited growth. Here, the growth falls under different effects of pollution: damage of people health, reduction of economic productivity, contraction of added value from agriculture etc. After the crises, on long term, the French economy remained tributary to the growth target, the pollution receiving a limited attention.

We emphasise that different environmental-growth hypotheses are found in the case of France, for a given period of investigation, which various from sub-periods to sub-periods, from short to medium and long time, under particular national and international economic contexts.

Regarding the policy implications, it is required for the French government to pay more attention on the environmental policies on medium and long terms. The adjustments which generate positive results on medium term should be implemented through the regional environmental policies, on the ground of international cooperation. On long term, the direct measures of the reduction of carbon emissions are good incentives for growth, but only during the favourable international economic contexts. Therefore, it is required for the French policy makers to sensitively control the carbon emissions-growth nexus, giving much more attention to the targeted time of needed effects and macroeconomic circumstances. Additionally, the focused policies for reduction of carbon emissions must prevail over economic growth maximizing.

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Appendix

Table A1: Summary statistics of variables

Variables	Ln(x)	Ln(y)
Mean	8.738693	0.555308
Median	8.773264	0.58504
Maximum	9.200374	0.731407
Minimum	8.071162	0.211159
Std. Dev.	0.341614	0.11398
Skewness	-0.3592	-1.36827
Kurtosis	1.911319	4.26805
Jarque-Bera	9.215433	49.27314
Probability	0.009975	0
Sum	1136.03	72.19
Sum Sq. Dev.	15.05429	1.6759
Observations	130	130

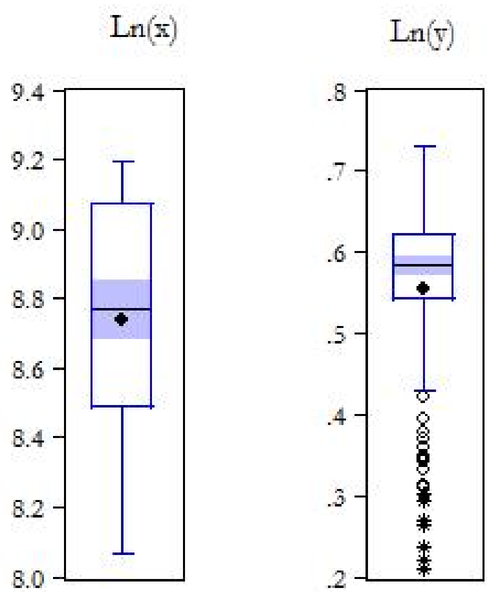

Figure A1: Box-plot of variables