Nexus between U.S Energy Sources and Economic Activity: Time-Frequency and Bootstrap Rolling Window Causality Analysis

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Abstract

This paper explores the relationship between U.S economic activity and renewable energy sources namely hydroelectric power, geothermal energy, wood energy, waste energy, biofuel, biomass energy, and total renewable energy. Monthly data for the period January 1981 to March 2015 is used to depict the comovements between the variables through Wavelet Squared Coherence (WTC) and Multiple Wavelet Coherence (MWCC) approaches. Maximal overlap wavelet correlation and cross-correlation measures, analogous to WTC and MWCC, show strong positive comovement in long-run. The causal linkage between economic activity and renewable energy sources is examined through bootstrap rolling window causality. The analysis reveals the significant reciprocal effects between the economic activity and energy use during the periods of extreme events. Overall, findings indicate that renewable energy sources play an important role in stimulating economic activity. This shows that present study has important implications for US energy policy authorities.

Keywords: Bootstrap rolling causality; economic activity; renewable energy sources; time-frequency analysis

I. Introduction

The rapid climate changes have increased the importance of exploration and usage of renewable energy sources (Kula, 2014). It has also been reported by International Energy Outlook (2010) that share of renewable energy would rapidly be increasing to world energy source due to fast growing industrial activity over the period of 2007-2035. The use of non-renewable energy sources is high compared to renewable energy sources but exploration of renewable energy sources is still a main concern of government policies (Apergis and Payne, 2012). Furthermore, it is pointed by Apergis and Payne (2010) that price volatility of fossil fuels such as oil and rise in energy pollutants due to rapid usage of fossil fuels have inclined the policy makers to explore alternative energy sources to meet rising demand of energy for sustainable economic development in long-run. To explore and develop alternate energy sources such as renewable energy sources[1], governments at global level have been providing tax credits for renewable energy production, subsidies as well as portfolio standards for renewable energy and other relevant policy initiatives have been adopted for renewable energy development (Kaygusuz 2007, Apergis and Payne 2012). The development of renewable energy sources may secure a country from foreign reliance to meet domestic energy needs, increase energy efficiency and secure the country form energy crisis, improve environmental quality and boost economic activity (Kalkos and Tzeremes, 2013).

The United States used renewable energy source such as wood to meet her 90% energy demand almost fifteen decades ago. With the passage of time, the United States became less reliant on wood energy due to rapid use of coal, petroleum and natural gas. The rise in environmental concerns have popularized the use of wood energy to meet energy needs in the United States today (EIA, 2014). The United States met 11% of total energy demand by using renewable energy sources in 2014 and renewable energy sources also used to generate 13% of total electricity over same period. More than 50% of electricity (from renewable energy sources) is generated from wood and waste (biomass energy) energy sources. Wood and waste energy sources are used for providing heat and steam to industrial sector as well space heating (EIA, 2014). Ethanol and biodiesel are also part of biomass energy are utilized for transportation activity. Furthermore, non-biomass renewable energy sources produce such as i.e. hydropower,

[1] Renewable energy sources are hydroelectricity, geothermal, solar, wind, biomass, wave, and tidal energy

geothermal, wind and solar[2] less greenhouse gas emissions compared to fossil fuels (EIA, 2013). The incentive provision of the US government doubled the consumption of renewable energy sources use over the period of 2000-2014. In 2014, solar arrays provide net metering facility to 43 states of the United States. The electricity generated from hydro energy sources is 6.2% of total electricity production in 2010 and is continuing to grow (EIA, 2013). The United States ranked 4 for hydroelectricity production in the world[3].

The American Outlook on Renewable Energy report (2007) indicated the reasons why the United States is moving for renewable energy sources: "*Americans need energy that is secure, reliable, improves public health, protect the environment, addresses climate change, create jobs, and proves technological leadership. American needs renewable energy. If renewable energy is to be developed to its full potential, America will need coordinated, sustained federal and senate policies that expand renewable energy markets, promote and deploy new technology; and provide appropriate opportunities to encourage renewable energy use in all critical energy market sectors: wholesale and distributed electricity generation, thermal energy applications, and transportation*". Later on, the US government announced officially in 2009 to expand renewable energy sources to its full potential for energy security and mitigation of climate change.

This inspires the researchers to examine the relationship renewable energy sources and economic activity either the US government initiatives to renewable energy sources promote economic activity or economic activity forces the US government to explore renewable energy sources. This study contributes in existing energy literature by: (i) the study investigates the relationship between renewable energy sources and economic activity for the US economy which has never empirically examined ever before. (ii) we have applied the series of wavelets such as continues, coherence, discrete and maximal overlap approaches to examine the correlation between renewable energy sources and economic activity. Aguiar-Conraria *et al.* (2008) have pointed out the two very important features of the wavelets analysis. First, the (discrete) wavelet transform has often been applied in the in most of the economic applications as a low and high pass filter. The economist find it hard to believe that these methods can provide better understanding of the

[2] Solar industry in the United States has provided employed 143,000 people.
[3] China, Canada and Brazil are larger producers of hydroelectricity production in the world.

data in comparison to the traditional techniques i.e. band pass filtering technique. Secondly, it is difficult to analyze two or more time series simultaneously. Most of the previous economic studies have either used this technique to examine individual time series or several time series individually. And the decomposition is then further studied by using the using the traditional time series methodologies e.g. correlation or Granger causality analysis (Aguiar-Conraria *et al.* 2008, p. 2865). The wavelet power spectrum deals with a single time series and helps to examine the variations in a time series at different frequencies and periods over different scales. The inability of wavelet power spectrum to deal with two time series have been overcome by Hudgins *et al.* (1993) and Torrence and Compo (2013) by developing the cross wavelet power and cross (squared) wavelet coherency, and phase difference. These techniques can deal with two time series by accommodating the time frequency analysis. These methods show the curbed covariance and correlation coefficient between different series in the time frequency space. The addition of phase term helps to examine the occurrence of pseudo cycle over the time. This phase difference also provides information regarding the lead-lag relationship between fluctuations of the two time series (Aguiar-Conraria *et al.* 2008, p. 2867). The continuous wavelet can also deal with the time series irrespective of the stationary properties. (iii), the direction of causality between renewable energy sources and economic activity is investigated by applying the rolling window Granger causality approach. We find the existence of positive strong co-movement in long-run confirmed by wavelets analysis. The bi-directional causality running from renewable energy to economic activity and vice versa is validated by the rolling causality analysis.

2. Literature Review

An interesting relationship of energy-growth nexus introduced by Kraft and Kraft (1978) who reported that economic growth is cause of energy consumption. The relationship between energy consumption and economic growth is still an area of interest for researchers, academicians and practitioners (Cho *et al.* 2016). The presence of causal association between energy consumption and economic growth provides policy guidelines not only at aggregated, sectoral levels but also at macro level (Salim *et al.* 2014). Existing energy literature provides numerous studies investigating the energy-growth nexus by using different indicator of energy consumption i.e. primary energy consumption, electricity consumption, non-renewable energy consumption and renewable energy consumption (Ozturk, 2010). Due to environmental concerns of non-renewable energy sources usage, countries have been moving to renewable energy sources to meet rising energy demand for sustainable economic development (Apergis and Payne, 2010a)[4].

The existing energy literature on renewable energy consumption-economic growth nexus provides four distinct hypotheses: (i) Growth hypothesis reveals that economic growth is cause of renewable energy consumption i.e. unidirectional causality running from renewable energy consumption to economic growth (Payne, 2010). In such situation, renewable energy consumption plays its vital role to promote economic activity and any reduction in energy supply (renewable energy) will impede domestic production and in resulting, economic growth is declined. This hypothesis empirically supported by Bobinaite *et al.* (2011) for Lithuania, Pao and Fu (2013) for Brazil, Magnani and Vaona, (2013) for Italy, Halkos and Tzremes (2013) for European countries, Ohler and Fetters (2014), Inglesi-Lotz, (2015) for OECD countries and Kula (2014) for global level, Tiwari *et al.* (2015) for Sub-Saharan Africa, Bhattacharya *et al.* (2016) for 38 countries and Ibrahim (2015) for Egypt reported that renewable energy consumption Granger cause economic growth. (ii) Feedback hypothesis reveals the bidirectional causal relationship between renewable energy consumption and economic growth. This shows that renewable energy consumption Granger causes economic growth and in return, economic growth causes renewable energy consumption in Granger sense. This indicates that both variables are interdependent and decline in renewable supply may decline economic growth which in resulting, declines renewable energy demand. The bidirectional causality between renewable energy consumption and economic growth is supported by Sadorsky (2009), Apergis and Payne (2010a, b), Apergis and Payne (2012a, b), Al-mulali *et al.* (2013), Lin and Moubarak (2014), Marques *et al.* (2014), Shahbaz *et al.* (2015), Cho *et al.* (2015) and Chang *et al.* (2015) for emerging economies, OECD countries, Eurasia, global level, 80 developed and developing countries, African countries, China, Greece, Pakistan, 80 countries and G7 countries respectively. This implies that development of renewable energy sources should be encouraged for sustainable economic development and environmental quality. In such situation, renewable energy supply would play vital role in stimulating economic activity and energy conservation policies must be discouraged.

[4] The usage of renewable energy sources may help in improving environmental quality by reducing energy pollutants.

Table-1: Summary of existing studies on renewable energy-growth nexus

No.	Author (s)	Country/Region	Variable	Methodology	Results
1.	Sadorsky, (2009)	Emerging Economies	Y, R	PVECM	$R \leftrightarrow Y$
2.	Apergis and Payne, (2010a)	OECD countries	Y, R, K, L	PVECM	$R \leftrightarrow Y$
3.	Apergis and Payne, (2010b)	Eurasia	Y, R, K, L	PVECM	$R \leftrightarrow Y$
4.	Apergis and Payne, (2011)	Central America	Y, R, K, L	PVECM	$R \leftrightarrow Y$
5.	Menegaki, (2011)	European countries	Y, R, E, M	PVECM	$R \neq Y$
6.	Bobinaite et al. (2011)	Lithuania	Y, R	GC	$R \rightarrow Y$
7.	Apergis and Payne, (2012a)	Global level	Y, R, K, L	PVECM	$R \leftrightarrow Y$
8.	Apergis and Payne, (2012b)	80 countries	Y, R, K, L	PVECM	$R \leftrightarrow Y$
9.	Tugcu et al. (2012)	G7 countries	Y, R, L, HC, RD	ARDL	$R \neq Y$
10.	Pao and Fu, (2013)	Brazil	Y, R, K, L	VECM	$R \rightarrow Y$
11.	Magnani and Vaona, (2013)	Italy	Y, R, K, L	PVECM	$R \rightarrow Y$
12.	Ocal and Aslan, (2013)	Turkey	Y, R	ARDL, VECM	$R \neq Y$
13.	Al-mulali et al. (2013)	African countries	Y, R	FMOLS	$R \leftrightarrow Y$
14.	Halkos and Tzremes (2013)	European countries	Y, R, K, L	CRSbc	R leads Y
15.	Ohler and Fetters (2014)	OECD countries	Y, R, K, L	PVECM	$R \rightarrow Y$
16.	Kula, (2014)	Global level	Y, R	PVECM	$R \rightarrow Y$
17.	Lin and Moubarak, (2014)	China	Y, R, E, L	ARDL, VECM	$R \leftrightarrow Y$
18.	Marques et al. (2014)	Greece	Y, R	VECM	$R \leftrightarrow Y$
19.	Salim et al. (2014)	OECD countries	Y, R, K, L	PMGC	$R \leftarrow Y$
20.	Inglesi-Lotz, (2015)	OECD countries	Y, R, K, M, RD	FE	R leads Y
21.	Shahbaz et al. (2015)	Pakistan	Y, R, K, L	ARDL, VECM	$R \leftrightarrow Y$
22.	Cho et al. (2015)	80 countries	Y, R, K, L	PVECM	$R \leftrightarrow Y$
23.	Tiwari et al. (2015)	Sub-Saharan Africa	Y, R	G-H	$R \rightarrow Y$
24.	Chang et al. (2015)	G7 countries	Y, R	T-Y	$R \leftrightarrow Y$
25.	Bhattacharya et al. (2016)	38 countries	Y, R, K, L	FMOLS	R leads Y
26.	Ibrahim, (2015)	Egypt	Y, R, FDI	ARDL, ECM	R leads Y

Note: Y→ economic growth, R → renewable energy consumption, K → capital, L → labor, M→ employment, E → CO_2 emissions, RD → research & development expenditures in energy and HC → human capital. Y ≠ R, Y → R, Y ← R, and Y ↔ R indicates no causality, from economic growth to renewable energy consumption, from renewable energy consumption to economic growth and feedback effect between renewable energy consumption and economic growth. CRSbc→ Constant Returns to Scale Bootstrap causality, VECM → vector error correction model, GC → Granger causality, G-Y → Granger and Yoon hidden cointegration approach, PVECM → panel vector error correction model, FE → fixed effect model, T-Y →Toda and Yamamoto.

On contrarily, (iii) Conservation hypothesis which reveals that economic growth is not cause of renewable energy consumption and may other factors determine economic growth. This shows that renewable energy consumption does not seem to play its role for enhancing domestic production and hence economic growth. In such situation, causality should be running from economic growth to renewable energy consumption and similar would not be true from opposite side. Renewable energy consumption is Granger cause of economic growth empirically supported by Salim *et al.* (2014) for OECD countries who noted the unidirectional causality running from economic growth to renewable energy consumption. Lastly, Neutral effect between renewable energy consumption and economic growth reveals no causal relationship between both variables. In Turkish economy, Ocal and Aslan (2013) reported that neither renewable energy consumption causes economic growth nor economic growth causes renewable energy consumption in Granger sense. This shows that energy conservation policies may not impede economic activity and hence economic growth because both variables are independent.

For the US economy, there are few studies investing relationship between energy consumption using disaggregated (energy sources), sectoral and aggregated data with conflicting empirical findings. At aggregated level, for example, Abosedra and Baghestani (1991) supported the findings of Kraft and Kraft (1978). Later on, Stern (1993) employed augmented production function to expose the relationship between energy consumption by applying VAR approach but found the neutral effect between the variables. Similarly, Stern (2000) reported a limited role of energy consumption in promoting US economic growth. Jin *et al.* (2009) incorporated energy prices in production function to test the association between energy consumption and economic growth by applying variance decomposition approach and impulse response function. Their analysis indicated the neutral role of energy consumption in economic growth process. Payne (2009) applied the Toda-Yamamoto causality for reinvestigating the association between energy (renewable and nonrenewable) consumption and economic growth. The results show that neither energy (renewable and nonrenewable) consumption causes economic growth nor economic growth causes energy (renewable and nonrenewable) consumption. Fallahi (2011) investigated the causal relationship between energy consumption and economic growth by applying Markov-switching vector autoregressive (MS-VAR) models. The results exposed that energy consumption and economic growth are interdependent i.e. feedback effect.

Hatemi-J and Uddin (2012) applied the bootstrap asymmetric causality between energy consumption and economic growth and their results showed that negative shock in energy consumption leads to negative shock in domestic output. Kocaaslan (2013) applied the Markov switching VAR model to investigate the direction of causal relationship between energy consumption and economic growth and reported that energy consumption causes economic growth. The results show that coal consumption is cause of economic growth and economic growth is caused by electricity consumption in Granger sense. Further, the feedback effect exists between energy consumption (natural gas, primary energy and renewable energy) and economic growth.

Table-2: Summary of studies on energy-growth nexus in the United States

No.	Author	Variable	Method	Growth Hypothesis	Feedback Effect	Conservation Effect	Neutral Effect
1.	Kraft and Kraft (1978)	EC, GNP	N.A	✓	…	…	…
2.	Abosedra and Baghestani (1991)	EC, GNP	GC	✓	…	…	…
3.	Stern, (1993)	EC, Y, K, L	J-C, GC	…	…	…	✓
4.	Stern, (2000)	EC, Y, K, L		…	…	…	✓
5.	Jin et al. (2009)	EC, EP, Y, K, L	VDC, IRF	…	…	…	✓
6.	Payne, (2009)	RE, NRE, Y	T-Y	✓	…	…	✓
7.	Fallahi, (2011)	EC, Y	MSC	…	✓	…	…
8.	Hatemi-J and Uddin (2012)	EC, Y	BAC	✓	…	…	…
9.	Kocaaslan, (2013)	EC, Y	MSC	✓	…	…	…

Note: Y → economic growth, GNP → gross national product, EC → energy consumption, K → capital, L → labor, EP → energy prices, RE → renewable energy consumption, NRE → non-renewable energy consumption, GC → Granger causality, J-C → Johansen cointegration, VDC → variance decomposition, IRF → impulse response function, T-Y → Toda and Yamamoto, MSC → Markov-switching causality, BAC → bootstrapping asymmetric causality.

At disaggregated level, Ewing *et al.* (2007) investigated the association between industrial production and energy consumption. They have applied various sources of energy such as total energy consumption, total renewable energy, coal, fossil fuels, hydroelectricity, solar energy, wood energy, gas consumption, alcohol, geothermal and waste. By applying variance decomposition approach, their empirical analysis indicated that shocks occurring in coal, gas and fossil fuels explain shocks stem in industrial output i.e. growth hypothesis. Sari *et al.* (2008) reexamined the linkages between energy consumption (disaggregated) and economic growth by applying the bounds testing approach to cointegration. They considered employment as an additional determinant of energy consumption and domestic production. They found that coal is negatively linked with industrial production but industrial production leads fossil fuels, hydroelectricity, waste, wind and wood. Furthermore, industrial production declines demand for solar and natural gas[5]. By applying Toda-Yamamoto Granger causality, Bowden and Payne (2009) examined the relationship between economic growth and energy consumption at disaggregated level. Their empirical analysis indicates the feedback effect between transportation energy consumption and real GDP and real GDP is also Granger cause of industrial energy

[5] Employment is negatively associated with industrial production, fossil fuels, hydroelectricity, waste and wind but positively linked with natural gas, solar and wood

demand[6]. The bidirectional causal relationship is noted between commercial energy consumption and real GDP and similar is true for residential energy consumption and real GDP. Yildirim *et al.* (2012) applied Toda-Yamamoto Granger causality and asymmetric causality to test the presence of causal relationship between economic growth and renewable energy sources. Their empirical analysis confirmed the presence of neutral effect between economic growth and kinds of renewable energy sources. Gross (2012) investigated the linkages between energy consumption and economic growth at sectoral level by applying the VECM Granger causality. The empirical findings indicated the conservation hypothesis in commercial sector but the feedback effect is noted in transportation sector. Recently, Tiwari (2014) probed the linkage between economic growth and energy consumption at disaggregated level by applying asymmetric Granger causality.

3. Methodology

3.1 Wavelet approaches

3.1.1 Continous wavelet approach and wavelet coherence

Wavelets are ‘small waves’ that grow and decay in a limited time period. The results from a mother wavelet i.e. $\psi(t)$ can be expressed as a function of two parameters: the first one shows where the wavelet is centered (τ*:* translation parameter) while the second indicates the analysis resolution (s*:* dilation parameter). Formally, wavelets are defined as:

$$\psi_{s,t}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)s \text{ with } \tau \in \Re \text{ , } s \neq 0. \quad (1)$$

To be a mother wavelet, $\psi_{s,t}(t)$ must have a zero mean, $\int_{+\infty}^{-\infty}\psi(t)dt = 0$ when squared, must be integrated to unity: $\int_{+\infty}^{-\infty}\psi^2(t)dt = 1$. This condition implies that $\psi(t)$ is limited to an interval of time. Furthermore, the continuous wavelet transform (hereafter, CWT) has the aptitude to decompose and reconstruct a given time series $x(t)$ — the admissibility condition — based on the following formula:

[6] Ziramba (2009) reported the feedback causality between oil consumption and industrial growth for South Africa.

$$x(t) = \frac{1}{C_\psi} \int_{+\infty}^{-\infty} \left[\int_{+\infty}^{-\infty} \dot{W}_x(s,\tau)\,\psi_{(s,\tau)}(t)\,d\tau \right] \frac{ds}{s^2}. \tag{2}$$

The CWT (denoted by C_ψ) also preserves time series characteristics, therefore:

$$\|x\|^2 = \frac{1}{C_\psi} \int_{+\infty}^{-\infty} \left[\int_{+\infty}^{-\infty} |w_x(s,\tau)|^2 d\tau \right] \frac{ds}{s^2}. \tag{3}$$

In the wavelet literature, various wavelet functions types are proposed including the Coiflet, Symmlet, Haar, Debauchies, and Gabor wavelets. Therefore, choosing the suitable wavelet is a critical matter since wavelet coefficients $W_{x,}(s,\tau)$ contain combined information on both the function *x(t)* and wavelet-based decompositions $\psi_{s,t}(t)$, the properties of used time series are crucial.

The most frequently used wavelet is undeniably the Morlet's wavelet introduced by Goupillaud *et al.* (1984). Formally, the Morlet's wavelet is given by:

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

where the term $e^{\frac{-\eta^2}{2}}$ guarantees the admissibility condition. Thus, for $\eta \geq 5$, the above-mentioned term becomes negligible and the Morlet wavelet is obtained as:

$$\psi_\eta(t) = \pi^{\frac{-1}{4}} \left(e^{i\eta t} \right) e^{\frac{-t^2}{2}}; \tag{5}$$

meanwhile, the Fourier transform of the true Morlet wavelet is given by:

$$\psi_\eta(f) = \pi^{\frac{1}{4}} \sqrt{2} e^{\frac{-1}{2}(2\Pi f - \eta)^2}. \tag{6}$$

The spectral density of time series across two-dimensional time scales can also be estimated using the wavelet power spectra (hereafter, WPS). Torrence and Compo (2008) compute white and red noise WPS and derive the corresponding distribution for the local wavelet power spectrum at each time *n* and scale *s,* as follows:

$$D\left(\frac{\left|w_n^x(s)\right|^2}{\sigma_p^2} \prec p\right) = \frac{1}{2} P_f \chi_\upsilon^2, \tag{7}$$

where the value of P_f is the mean spectrum at the Fourier frequency f corresponding to the wavelet scale s and where υ is equal to 1 or 2 for real or complex wavelets, respectively.

WTC can be defined as the ratio of cross-spectrum to the product of the spectrum for each series and can be viewed of as local correlation between two time series in the time-frequency dimension (Aguiar-Conraria *et al*. 2008)). Thus, a WTC value close to one shows high degree of synchronization between time series but a WTC value close to zero implies no relationship. Although the WPS describes time series variance, with times of large variance showing large powers, the cross-wavelet power of two time series depicts the covariance between these time series at each scale or frequency. The WTC isolates regions in the time-frequency domain where the stated time series co-move, even if they may not exhibit a common high power.

Following Goupillaut et al. (1984), the cross-wavelet transform of two time series x(t) and y(t) is defined as follows:

$$W_{xy}(\tau,s)= W_x(\tau, s)\, W^*{}_y(\tau, s), \tag{8}$$

In the eqution-8, $W_x(\tau, s)$ and $W_y(\tau, s)$ designate the CWTs of x(t) and y(t), respectively. τ is a position index indicating the scale and the symbol * refers to a complex conjugate. The cross-wavelet power can easily be calculated using the cross-wavelet transform as $|W_{xy}(u, s)|$. Torrence and Webster (1999) define the squared wavelet coherence (hereafter, SWC) coefficient as follows:

$$R_t^2(s) = \frac{\left|S\left(s^{-1} W_t^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_t^X(s)\right|^2\right) \cdot S\left(s^{-1}\left|W_t^Y(s)\right|^2\right)}, \tag{9}$$

S is a smoothing operator. WTC can be considered as a correlation coefficient localized in the time-frequency domain with a value that ranges between 0 and 1 (see e.g. Grinsted *et al*. 2004).

3.1.2 Wavelet Multiple coherence

The multiple wavelet coherence (MWC) can be perused as a generalization of the bivariate coherence approach this it enables us to depicts the co-movement between a set of independent time series across time scales. Obviously, the MWC is more flexible than the standard WC since it encompasses the higher dimensionality of the data. Following Huang *et al.* (2016), the MWC is defined as follow:

$$RM^2(x,y,z) = \frac{R^2(y,x)+R^2(y,z)-2Re\,[R(y,x).R(y,z)^*.R(x,z)^*]}{1-R^2(y,z)} \qquad (10)$$

The mentioned ratio is the squared result of the MWC of three time series (including IPI and two kinds of renewable energy assets). $R(y,x)^2$, $R(y,z)^2$ and $R(x,z)^2$ are the wavelet squared coherence between each combination of pairs.

3.1.3. The maximal overlap wavelet

The maximal overlap wavelet is a discrete wavelet transform (WDT) and has several names in the wavelet literature such as the “non-decimated DWT”, the “stationary DWT”, the “translation-invariant DWT” and the “time-invariant DWT” (e.g. Nason and Silverman, 1995; Coifman and Donoho, 1995). While wavelet coefficients are related to non-overlapping differences of weighed averages from the original signal in the case of WDT, the MODWT algorithm computes all the shifted time intervals describing overlapping differences (considering all possible differences) at each scale and thus allows us to obtain the maximum amount of information about the variability of the signal. The number of wavelet and scaling coefficients at every scale is equal to the original number of observations. The MODWT filter is obtained directly from the discrete wavelet transform (DWT) filter. Thus, the MODWT scaling $\breve{\varphi}_{j,k}$ and wavelet $\breve{\psi}_{j,k}$ filters are given by:

$$\breve{\varphi}_{j,k} = \frac{\varphi_{j,k}}{2^{2/j}}$$

$$\breve{\psi}_{j,k} = \frac{\psi_{j,k}}{2^{j/2}} \tag{11}$$

For a time series, X with arbitrary sample size N, the J[th] level MODWT scaling $\tilde{\upsilon}_{j,t}$ and wavelet $\tilde{w}_{j,t}$ coefficients are obtained using the following formulas:

$$\tilde{w}_{j,t} = \frac{1}{2^{\frac{j}{2}}} \sum_{l=0}^{L-1} \tilde{h}_{j,l} X_{t-l} \tag{12}$$

$$\tilde{\upsilon}_{j,t} = \frac{1}{2^{\frac{j}{2}}} \sum_{l=0}^{L-1} \tilde{g}_{j,l} X_{t-l}$$

3.1.4 The correlation and cross wavelet cross correlation

In this section, we provide a brief description of the maximal overlap wavelet correlation and cross correlations, useful for assessing the main lead/lag relationships between economic activity and energy consumption.

Wavelet variance has proven to be useful in providing an accurate scale-based decomposition of the time-varying sample variance (Serroukh *et al.* 2000). Let X_t be a second-order stationary stochastic process with zero mean. As the wavelet variance decomposes the variance of x_t on a scale-by-scale basis (see Percival, 1995), the wavelet variance at scale τ_j is given by:

$$\sigma_{X,j}^2 = \frac{1}{2\tau_j} Var(w_{j,t}) \,, \tag{13}$$

where $\tau=2j-1$ and $w_{j,t}$ is the wavelet coefficient (defined below). The estimated wavelet variance of x_t for a given scale s_j can also be expressed in terms of the normalized sum of the squared wavelet coefficients as:

$$\tilde{\sigma}_{x,}^2(\tau_j) = \frac{1}{N_j 2^J} \sum_{t=0}^{N_j-1} w_{j,t}^2 = \frac{1}{N} \sum_{t=0}^{N_j-1} \tilde{w}_{j,t}^2 \,. \tag{14}$$

Overall, the MODWT variance estimator is efficient given its flexible properties (see Gallegati 2008). The MODWT provides a straightforward solution to the tricky problem of time series boundary effects. For the stochastic processes X_t and Y_t, wavelet covariance for scale *j* is defined as:

$$\gamma_{XY}\left(\tau_j\right)=Cov(\tilde{\omega}^{X}_{j,t}\tilde{\omega}^{Y}_{j,t})\,. \tag{15}$$

The MODWT covariance between X_t and Y_t can be expressed in terms of the wavelet coefficients at different scales *j by:*

$$\tilde{\gamma}_{XY}\left(\tau_j\right)=\frac{1}{N}\sum_{t=0}^{N_{j-1}}\tilde{\omega}^{X}_{j,t}\tilde{\omega}^{Y}_{j,t}\,. \tag{16}$$

Finally, the cross-covariance and its normalized version for scale τ_j at lag λ is given as follows:

$$\tilde{\gamma}^{XY}_{\lambda}\left(\tau_j\right)=\frac{1}{N}\sum_{t=0}^{N_{j-1}}\tilde{\omega}^{X}_{j,t}\tilde{\omega}^{Y}_{j,t+\lambda}\,, \tag{17}$$

$$\tilde{\rho}^{XY}_{\lambda}\left(\tau_J\right)=\frac{\tilde{\gamma}^{XY}_{\lambda}\left(\tau_j\right)}{\tilde{\sigma}_X\left(\tau_j\right)\tilde{\sigma}_Y\left(\tau_j\right)}\,. \tag{18}$$

3.2. The bootstrap Rolling MWALD causality test

Following Balcilar *et al.* (2010) and Tang (2013, 2015), we apply the bootstrapping rolling causality test to the pair wised IP-renewable energy consumption. The mentioned method is enough flexible to adequately capture the time varying causality features. Zapata and Rambaldi (1997) stated that the MWALD is more feasible because of its simplicity and its higher performances in larger samples. Furthermore, Mantalos (2000) proved that bootstrap test exhibits the highest accuracy in all estimates regardless of the cointegration properties. These pioneer findings motivates our choice of the bootstrap MWALD test which relies on the following bivariate VAR(2) specification:

$$\begin{pmatrix} lnIP_t \\ lnEC_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{bmatrix} \varphi(L)_{11} & \varphi(L)_{12} \\ \varphi(L)_{21} & \varphi(L)_{22} \end{bmatrix} \begin{pmatrix} lnIP_t \\ lnEC_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{19}$$

$lnIP_t$ and $lnEC_t$ are the logarithm of IP and renewable energy consumption respectively while $\varepsilon_1, \varepsilon_2$ are assumed to follow a white noise process with zero mean and non singular covariance matrix. $\varphi(L)_{ij} = \sum_{k=1}^{p} \varphi_{ij,k} L^k$, I, j=1, 2 and L is the lag operator defined in the bivariate framework. The null hypothesis that IP index not Granger causes a given renewable energy consumption can be tested by imposing zero restrictions i.e. $\varphi_{21,j} = 0$ for $i = 1,2 \ldots p$. The optimal number of lag L is determined by the information criteria (AIC).

4. Empirical Results

4.1. Data Overview

The study uses monthly data of Industrial Production Index (IP) and renewable energy sources namely Hydroelectric Power Consumption (HPC), Geothermal Energy Consumption (GEC), Wood Energy Consumption (WEC), Waste Energy Consumption (WaEC), Biofuel Consumption (BiEC), Total Biomass Energy Consumption (BEC), and Total Renewable Energy Consumption (REC) of U.S for the period January 1981 to March 2015[7]. The IPI data is extracted from International Financial Statistics (CD-ROM, 2015) and data of renewable energy sources is obtained from the US Energy Information Agency (https://www.eia.gov/). Table-3 reports the descriptive statistics of the variables.

Table-3: Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB Stats.
IPI	77.516	83.971	106.30	46.831	17.765	-0.1784	1.5334	39.014***
HEC	239.74	236.55	357.38	145.71	45.772	0.2756	2.4019	11.329***
GEC	13.299	14.500	19.684	3.2200	3.9777	-0.8805	2.8064	53.752***
WEC	189.49	184.54	252.90	128.70	23.845	0.2089	2.1172	16.336***
WaEC	33.491	35.307	54.461	6.7440	10.621	-0.7984	3.0513	43.711***
BiEC	47.521	16.867	182.65	0.9760	56.742	1.2593	2.9532	108.66***
BEC	270.50	253.23	417.84	178.54	53.158	1.0890	3.2220	82.086***
REC	554.89	528.61	867.50	395.40	102.10	1.2380	3.9821	121.49***

Note: *** indicates the rejection of null hypothesis of normality at 1% level of significance. JB stands for Jarque-Bera test.

4.2 Wavelet power spectrum and bias correction

An adequate application of the wavelet decomposition approach corrects the so called "bias problem". This may arise toward the low frequency oscillations not only in the wavelet power spectra but also in the wavelet cross spectrum (Liu et al. 2007, Veleda et al. 2012). Following Ng and Chan (2012), the bias problem is rectified for the industrial production index as well as the

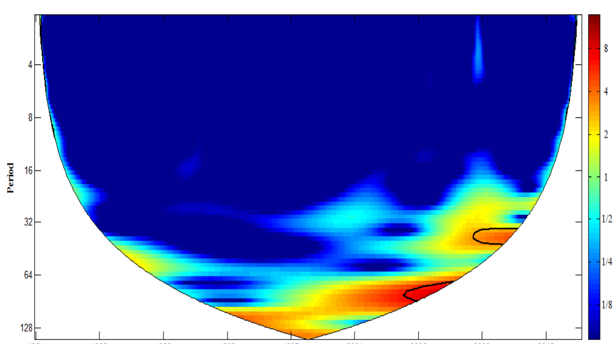
[7] We have used renewable energy supply. It is understood that all renewable energy is consumed which is produced by utilizing different sources of renewable energy.

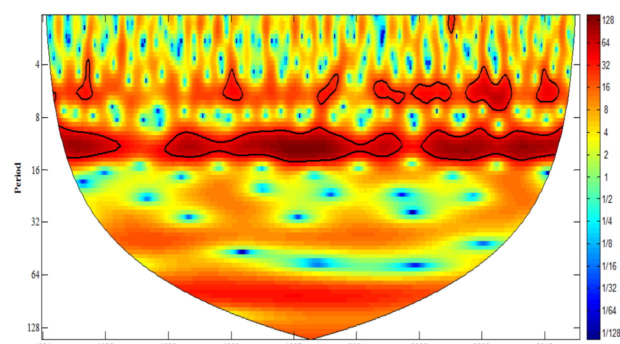
seven involved renewable energy sources. Figure-1 shows their respective wavelet power spectrum.

Following the standard practice, we use contour plots to present the wavelet power and coherence spectrum. The contour plots approach involves three dimensions: period, time and wavelet coherence power. The period and time are denoted on vertical and horizontal axes but the level of similarity is indicated by color coding respectively that ranges from blue (low similarity) to red (high similarity). The thick black continuous line in Figure-1 presented above isolates regions where the wavelet squared coherence is statistically significant at 5% level. Comparatively, biofuel energy consumption and industrial production power spectra are almost governed by the blue color over the whole sample and from lowest to highest frequencies. This implies that these two indices not depict intense variations across time scales and are relatively stable. Hydroelectric energy consumption depicts significant drifts as the red color is omnipresent regardless of the frequencies. This shows the continuum of red vortices compressed to each other's located inside the cone of significance underlining the importance of specific abrupt changes occurred from the short to the long run. Wood, waste and biomass energy consumption have similar behavior showing a sharply disintegrating red vortices at high frequencies thus implying a short lived drifts.

a). Industrial Production Index (IP)

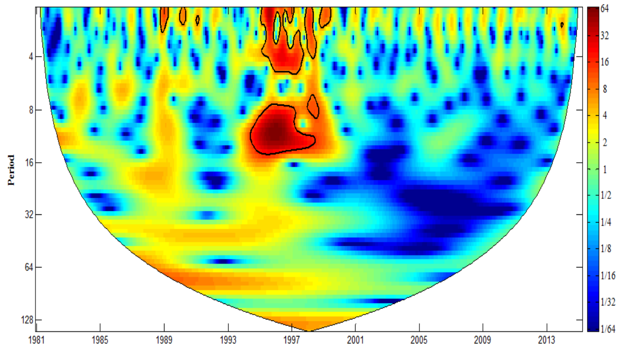
b). Hydroelectric Power Consumption (HPC)



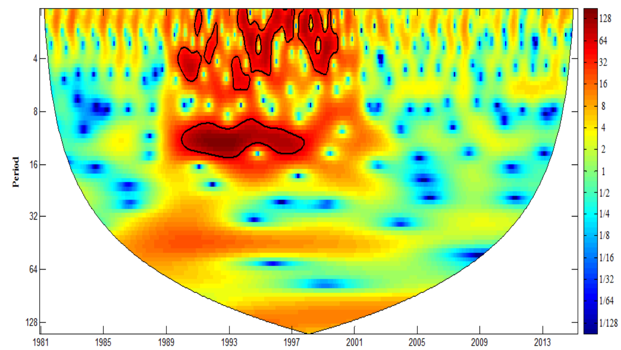


c). Geothermal Energy Consumption (GEC)

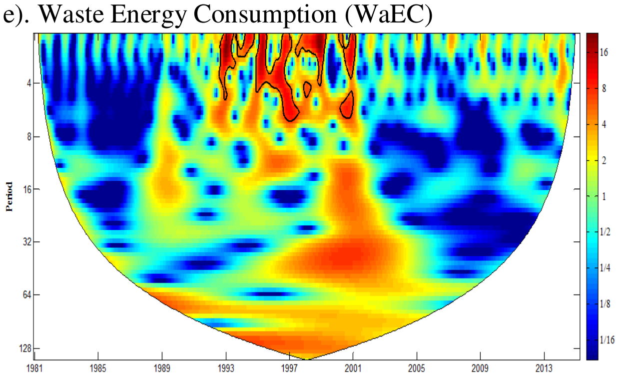
d). Wood Energy Consumption (WEC)



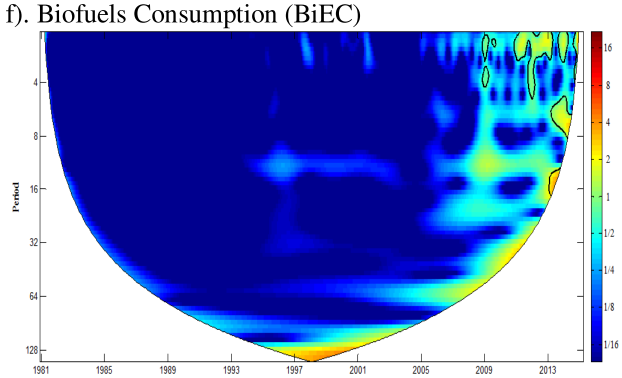
e). Waste Energy Consumption (WaEC)



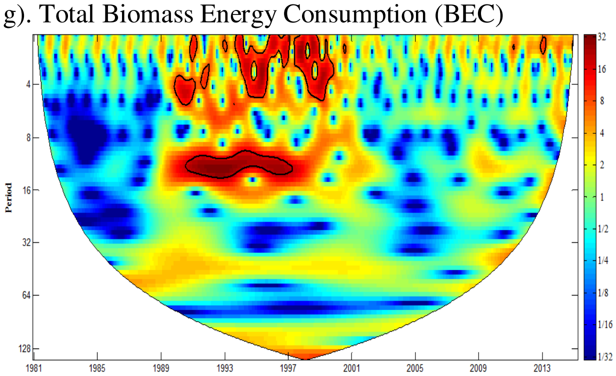
f). Biofuels Consumption (BiEC)



g). Total Biomass Energy Consumption (BEC)



h). Total Renewable Energy Consumption (REC)



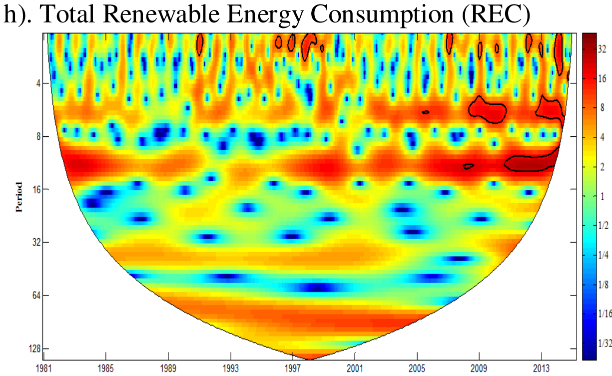


Figure-1: Wavelet power transform

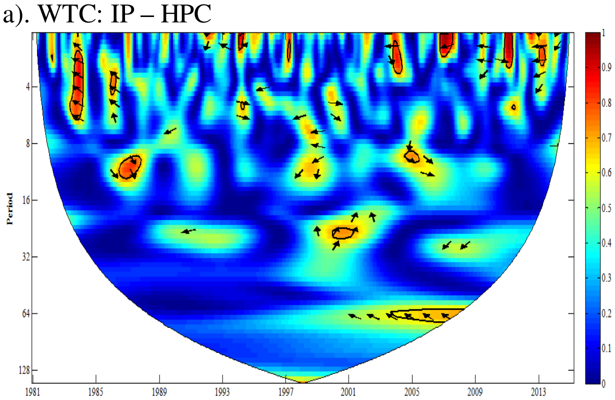
4.3. Wavelet coherence analysis

To better assess the co-movement patters of the pair wised industrial production and the seven renewable energy sources indices, we rely on the wavelet bivariate coherence (WTC) and multiple coherence (WMC). This latter allows capturing the multivariate aspects of interactions between the involved variables.

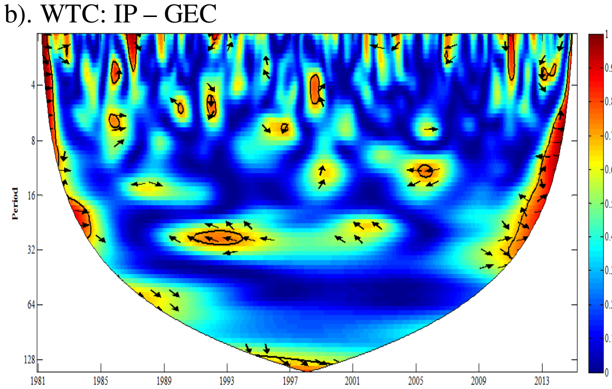
The wavelet squared coherence plots for the seven pair wised IP- renewable energy sources are conveyed in Figure-2. In Figure-2 arrows pointing towards left (right) means a negative (positive) relationship between the pairs. Throughout the visual inspection, we identify a weak relationship between IP and renewable energy source over the whole sample as indicated by the islands of blue color (i.e. low level of coherence). Additionally, we note quite similar pattern across the pairs. This weak co-movement is evident at the higher frequencies (top of the graphs) between 2 and 16 months. However, significant positive co-movement is located at low frequencies (bottom of the graphs) especially during the start and the end of sample period. It is worth noting that positive interactions are depicted at low and middle frequencies since some red vortices were detected between 16 and 128 trading months. The red areas are disconnected from each other as they are cut by the blue zones. This mainly proves the occurrence of abrupt changes over the whole period for all pairs and underlines the plausible inversion of the tendency of co-movements between the given variables. This implies that IP and renewable energy sources are expected to commove over different frequencies and across different time scales. In other words these markets tend to be aligned in long-run regardless of renewable energy source.

The most intense positive interactions, as the red color have long lasting durations; occur between IP-WaEC and IP-BiEC pairs during the beginning of sample period while IP-WEC and IP-BEC pair show high significant interaction towards the end of sample period. These pairs may exhibit a convergent pattern thus co booming or co crashing together. This finding is important since it prove that an increase in the industrial production will induce a substantial increase in the consumption of these specific energy sources in long-run. In other word, the consumption of these energy sources may contribute towards the industrial production in US.

a). WTC: IP – HPC

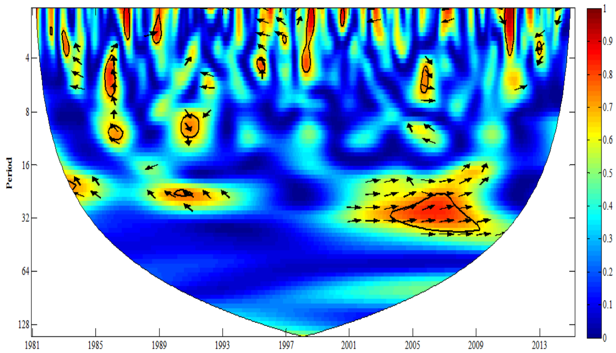


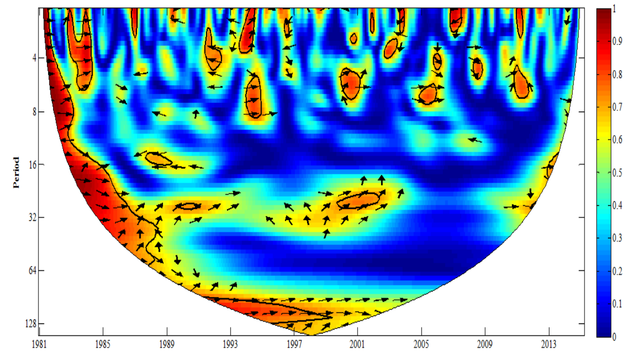
b). WTC: IP – GEC



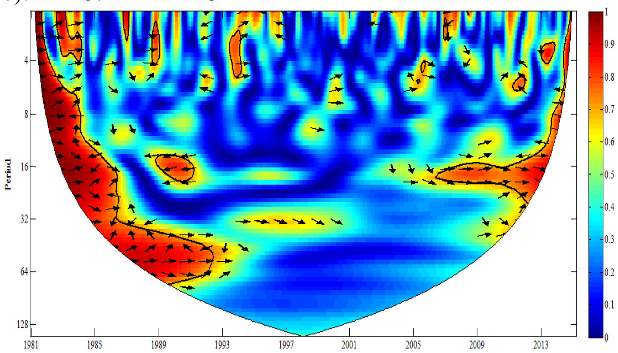
c). WTC: IP – WEC

d). WTC: IP – WaEC

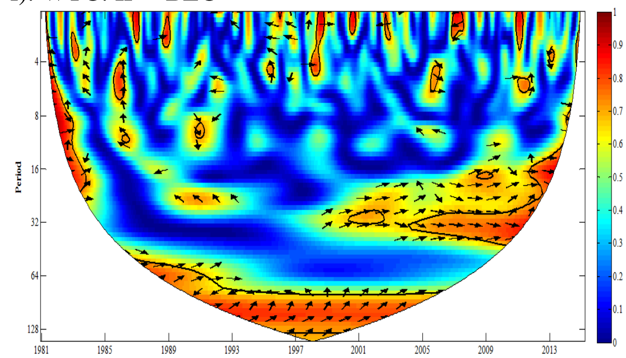




e). WTC: IP – BiEC



f). WTC: IP – BEC



g). WTC: IP – REC

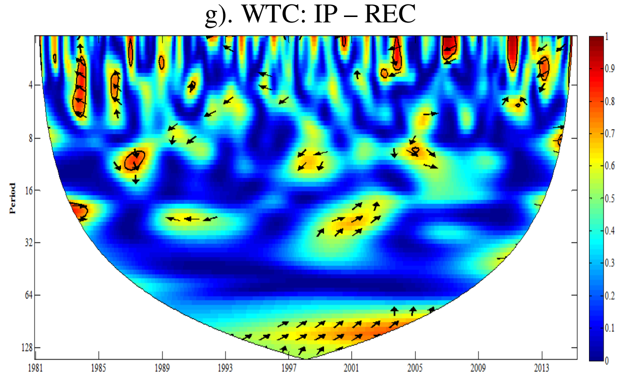


Figure-2: Wavelet squared coherence

The WMC plots between the IP, WoEC and BEC as well as IP, WaEC and BiEC triplets are shown in Figure-3. We focalize the attention only on these indices since they especially exhibited positive co-movements. Interestingly, the co-movement between the three variables follows a heterogeneous pattern over time and frequency. The strength of interactions varied when moving from the high frequency to the low frequencies. It is easily remarkable how the high frequency (between 2 and 8 months) is governed by a succession of disconnected small vortices with color migration from blue to yellow. The given anomalies reflect weak co-movements. In addition, some yellow-red small areas appeared sharply disintegrating at the highest frequencies. The lowest frequencies are already governed by strong positive co-movement that reaches its zenith at both extremities of figures (in Figure-3). These vortices are dispersed on the whole sample period, likely proving the strong interplays between the considered triplets across time scales. Obviously, striking similarities are detected across the triplets with reference to the blue color but there is a clear difference when dealing with the positive co movements. It seems that an increase in the industrial production will trigger much more the increase of waste and biofuel energy than wood and biomass energy. Overall, we find that increasing the level of industrial production (may be by adopting a new production technology or by modernizing the existing one) push the economy to higher consumption levels of particular energy resources, therefore a rigorous monitoring of their degradation should be undertaken to avoid any future shortage.

a). IP Vs. WoEC and BEC   b). IP Vs. WaEC and BiEC

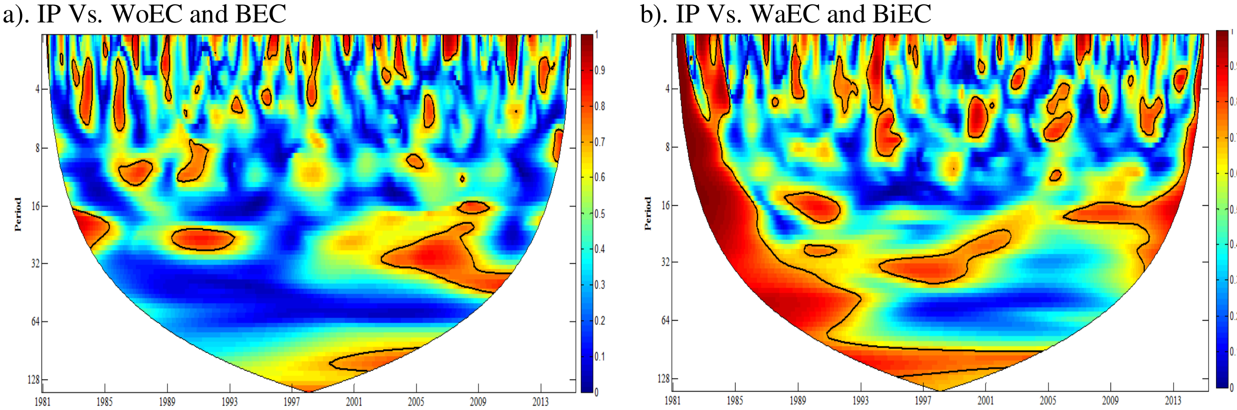


Figure-3: wavelet multiple coherence

4.4. Maximal overlap wavelet correlation and cross correlation analysis

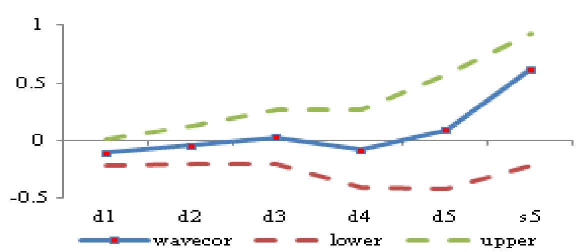
To further assess the primary findings provided by WTC and WMC methods, we rely on the discrete wavelet approach. Thus the maximal overlap wavelet correlation and cross correlations are estimated for each pair wised data[8].

In spite of its wide use, the maximal overlap wavelet has flexible properties (See e.g. Gallegati 2008, 2012) allowing it to be the best suitable to adequately encircle the dynamic interplays between the given variables across time scales. The overall aim of this section is to elucidate the wavelet correlation between the mentioned variables across monthly time scale periods. The

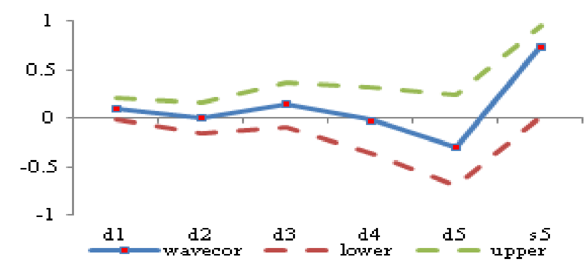
[8] IPI and each Energy Consumption index was decomposed via the MODWT by using the LA(8) FILTER. The decomposition level was fixed to 5 (the choice of the optimal decomposition length is based on the formula provided by Donoho (1995) as follow: L= $\log(T)^2$) . We obtained up to five details (d_1 = 2-4 months, d_2=4-8 months, d_3=8-16 months, d_4=16-32 months and d_5=32-64 months) and a smoothed trend noted S_5

pair-wise correlation coefficients were computed as in equation-19 and are reported in Figure-4 where the blue line track their evolution while the dotted green and red lines show the upper and lower band for the 95% confidence interval. The strength of correlation can be classified into four types as economic activity-renewable energy consumption may be strongly correlated (between 0.5 and1) modestly correlated (below 0.5), less correlated (between 0 and 0.5) or anti – correlated (negative correlations). A visual inspection of the graphs suggests that all the pairs have a common increasing trend of correlation from short-run to long-run. In other words, all the series are likely to converge by adopting homogenous alignments in long-run. The correlation increases in crescendo with weak variations around the zero line in the short and middle term but register a meaning full jump at the coarser scales. More precisely, the level of correlation is negligible given the weak amplitudes but when reaching the last scale, the correlation feature clearly switched to become very close to unity. Given that all IP-renewable energy sources display highly positive correlations in long-run, we may expect that an overall increase of industrial production may cause a rise in renewable energy demand as previously supported by the WC and WMC approaches.

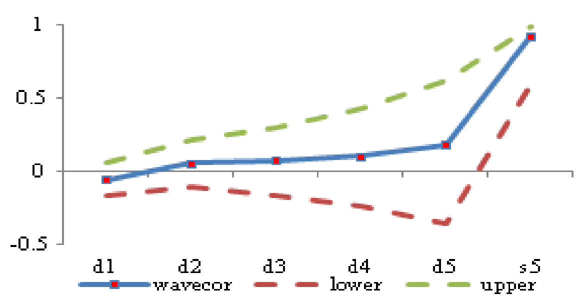
a). MODWT WC: IP – HPC



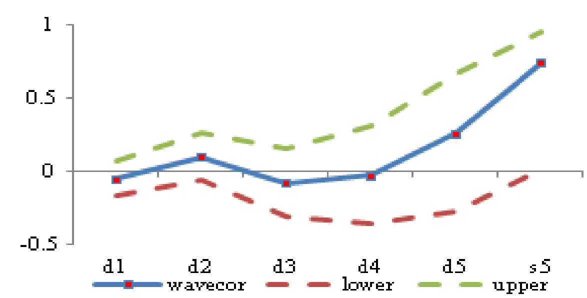
b). MODWT WC: IP – GEC



c). MODWT WC: IP – WEC

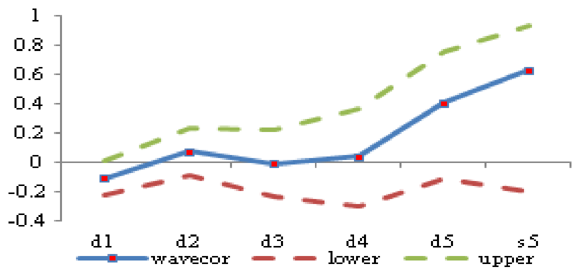


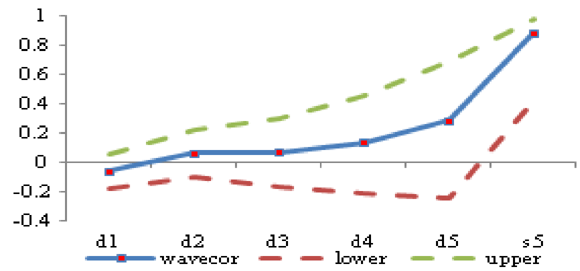
d). MODWT WC: IP – WaEC



e). MODWT WC: IP – BiEC

f). MODWT WC: IP – BEC





g). MODWT WC: IP – REC

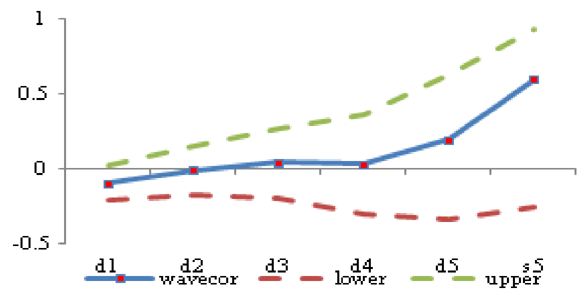


Figure-4: Maximal overlap wavelet correlations for the Pair-wise IP–Renewable Energy

The Wavelet Cross-Correlations (WCC) estimates will serve to check the consistency of previous findings thus the CCF plots of IP-renewable energy pairs are exposed in Figure-5 to 11. The time delay between the two signals is chosen to include 12 lags. Such lead-lag relationship implies a sufficiently large time delay of one year (12 months) allowing for a richer exploration of lead lags patterns. Knowing that the response of IP to renewable energy sources or vice versa may not occur immediately in the first lags, the most intense attractions may appear after N months that's why this choice seems reasonable enough to capture possible significant cross correlations effects across time scales.

To facilitate the reading of the wavelet CCF curves, it is important to note that the right half of each figure corresponds to the leading effects played by IP that drives renewable energy consumption while the left half describes the leading role of renewable energy source when IP becomes the follower. A close look at figures reveals almost a similar shape of cross correlations patters across the pairs. It is easily remarkable how the cross-correlations tend to stabilize at coarser scales while more drifts /spikes are located at the finest scales. The CC curves become smoother at scale 4 and 5 regardless of the IP-renewable energy combinations meaning that the attractions forces are less contaminated by abrupt changes approximately after 16 -64 months. At scale 1, numerous compressed peaks are detected reflecting the great instability of the interactions between each pair wised IP-renewable energy source at both sense. This also highlights the reciprocal dominance of a given index on the other by exerting significant lead/lag effects. Higher are the number of peaks in the left/right regions more intense is the driving force played by the leading indicator, thus if significant number of successive oscillations are located on the extreme right, it implies that IP is likely to lead renewable energy consumption (each series) while the reverse intensity of causation is confirmed if the peaks are concentrated on the extreme left. Depending on the pair, CC intensity is reduced when the short run fluctuations completely disappear at scale 4 (16-32 months) since the curves almost merge with the horizontal axis. Obviously, the middle run can be perceived as a transitory period where there is neither leader nor follower. Even, if the causal links are found, they are relatively weak given that oscillations are slightly below or above the zero line (almost between -0.2 and 0.2 amplitudes). The amplitude of CC reach their zenith after five years (64 months) but the influential role of IP on a given renewable energy or vice versa is relatively weak since it ranges between -0.5/-0.4 and 0.4/0.5. These results also corroborate the previous findings as they testify on the changing patterns of lead lag relationship than can be either positive or negative.

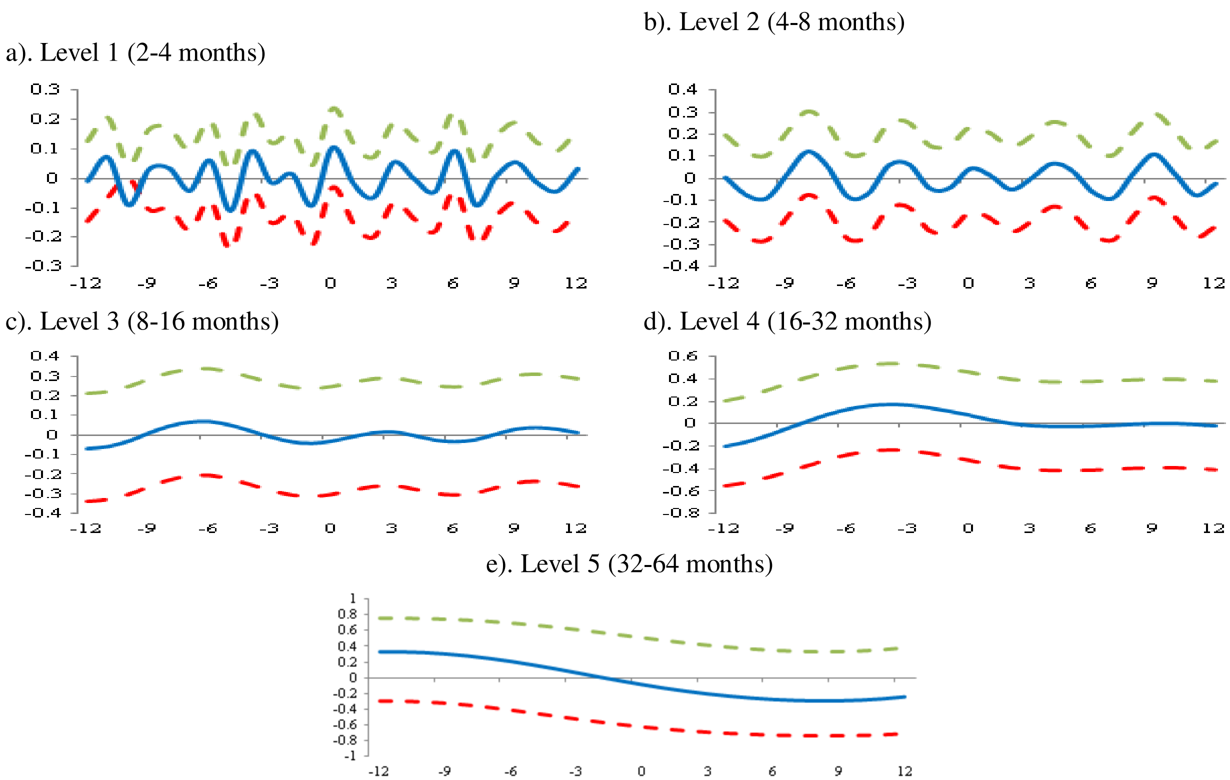
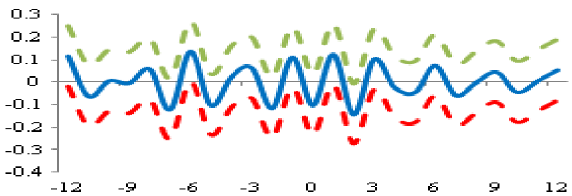
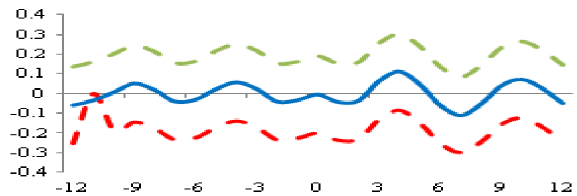


Figure-5: WCC IP-HPC

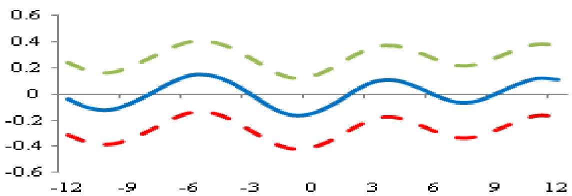
a). Level 1 (2-4 months)



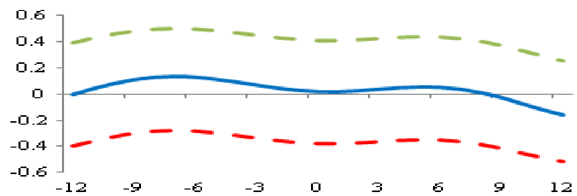
b). Level 2 (4-8 months)



c). Level 3 (8-16 months)



d). Level 4 (16-32 months)



e). Level 5 (32-64 months)

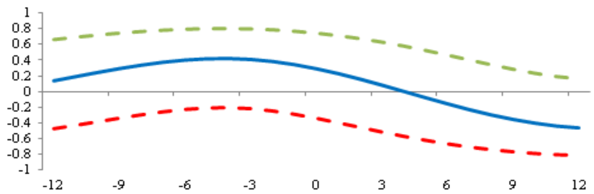
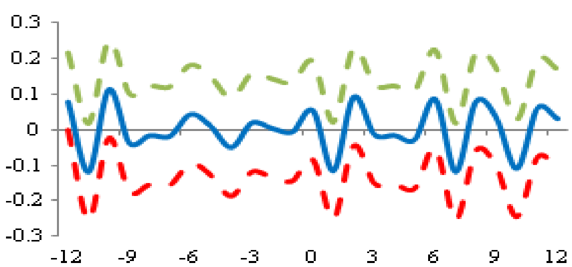
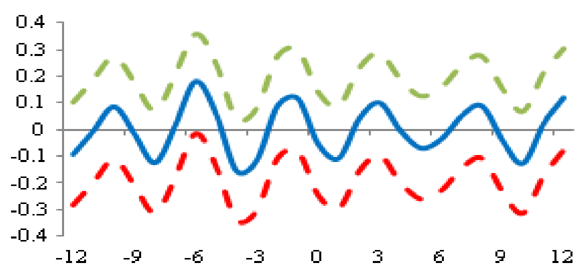


Figure-6: WCC IP-GEC

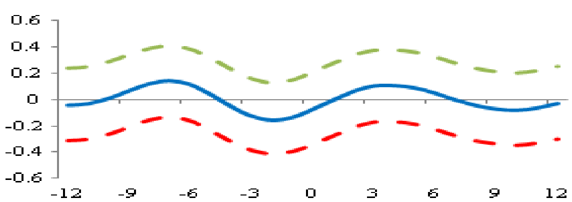
a). Level 1 (2-4 months)



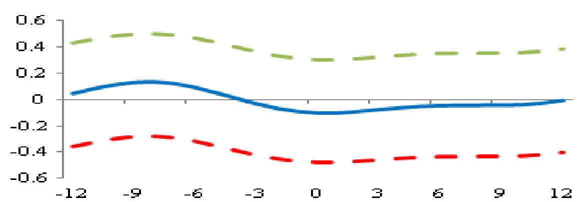
b). Level 2 (4-8 months)



c). Level 3 (8-16 months)



d). Level 4 (16-32 months)



e). Level 5 (32-64 months)

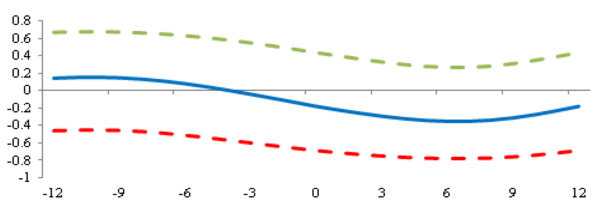
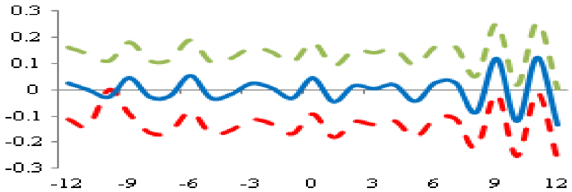
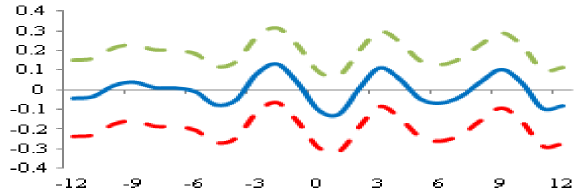


Figure-7: WCC IP-WEC

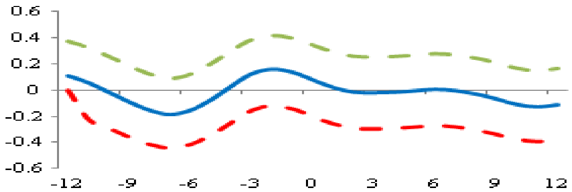
a). Level 1 (2-4 months)



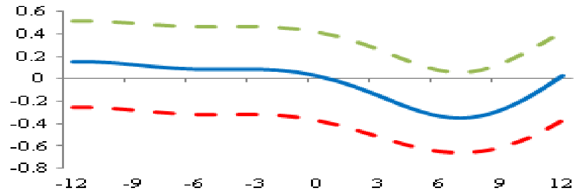
b). Level 2 (4-8 months)



c). Level 3 (8-16 months)



d). Level 4 (16-32 months)



e). Level 5 (32-64 months)

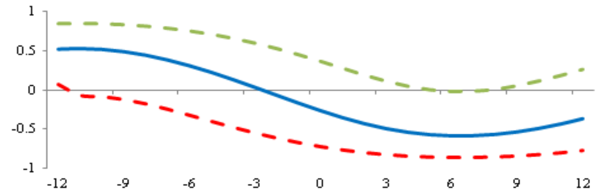
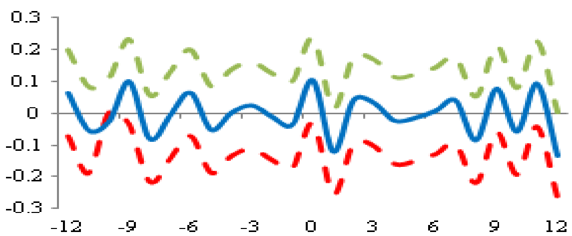
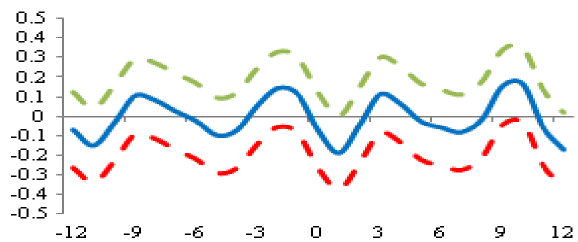


Figure-8: WCC IPI – WaEC

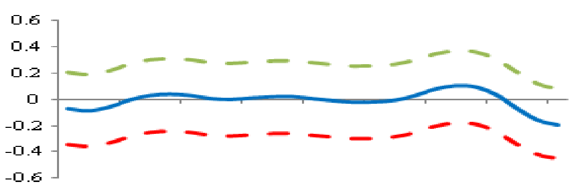
b). Level 2 (4-8 months)

a). Level 1 (2-4 months)

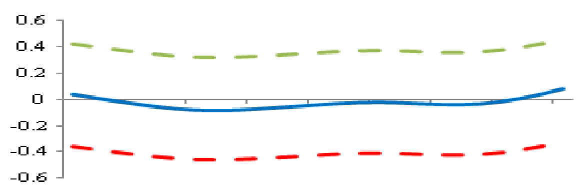




c). Level 3 (8-16 months)



d). Level 4 (16-32 months)



e). Level 5 (32-64 months)

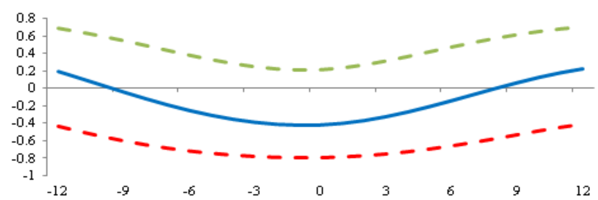


Figure-9: WCC IPI – BioEC

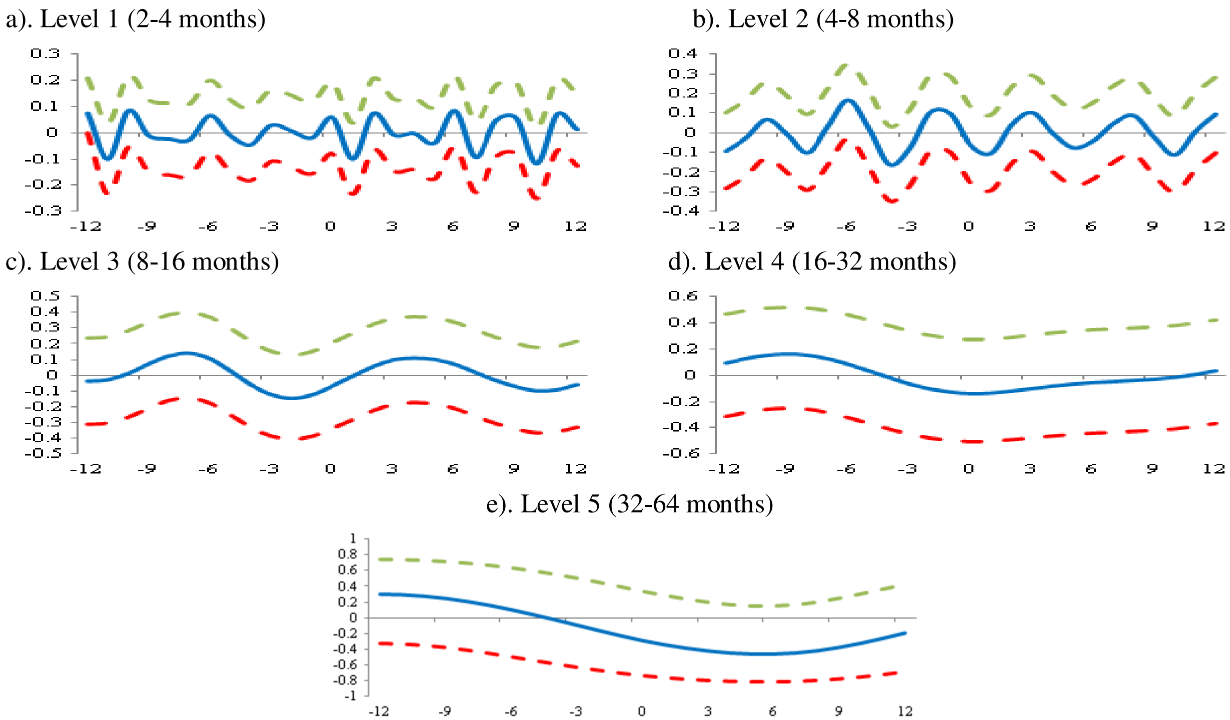


Figure-10: WCC IPI - BEC Pair

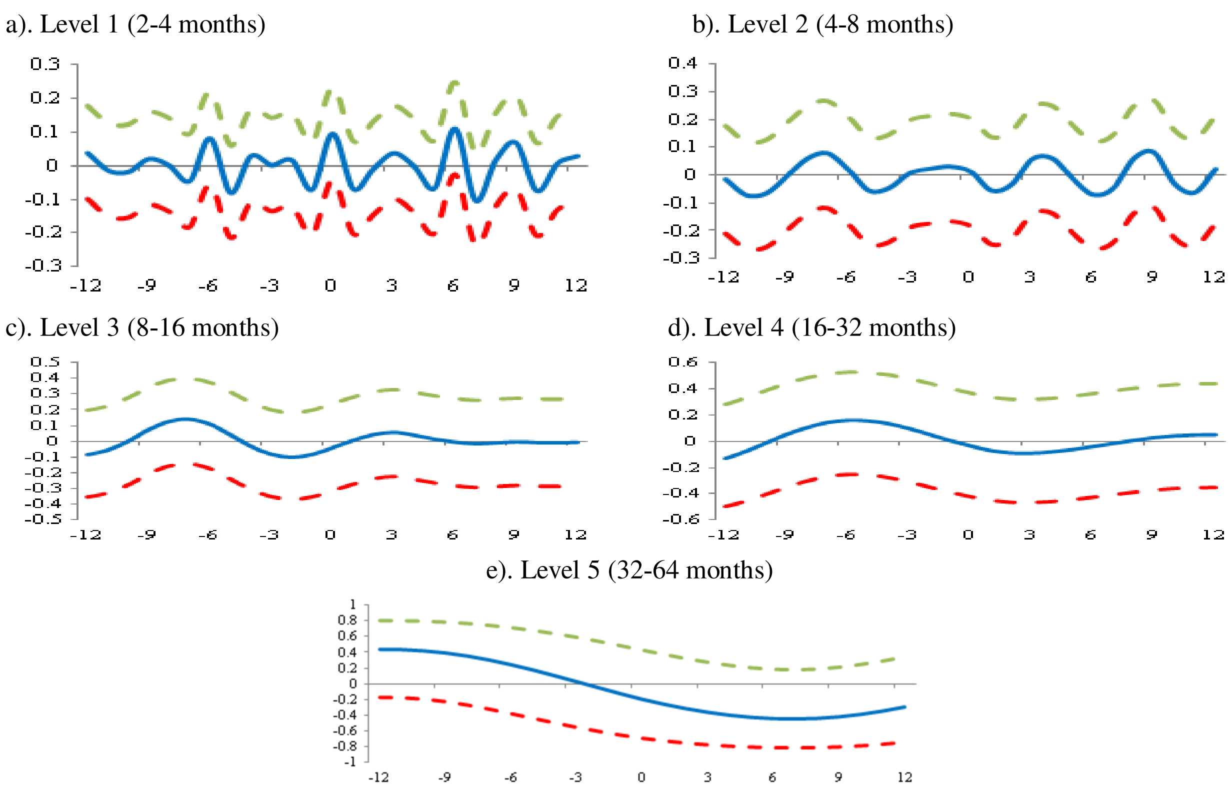


Figure-11: WCC IPI - REC Pair

4.5. Time varying rolling window results

There are two worth noting points from the findings of previous analysis, 1). The relationship between the IP and renewable energy sources varies over the sample period. 2). The wavelet framework mainly relies on the correlation dynamics to capture the interplay between the variables. Although wavelet based analysis have several advantages over traditional econometric techniques, as mentioned in previous sections, yet does not provide the cause and effect relationship between the variables of study. To overcome this limitation and given that the relationship between IP and renewable energy sources varies over time, we rely on MWALD rolling causality test recently applied by Tang (2013) and Tang *et al.* (2015). This method is based on a bivariate VAR specification (see equation-22). We have applied MWALD rolling causality test to verify the bivariate causality between IP and all kinds of renewable energy consumption. Table-4 reports the full sample causality estimates for both causality directions thus when IP may lead renewable energy sources (right panel) or when IP follows renewable energy sources (left panel). At each case, we report the LR statistics and p-values obtained through 2000 bootstrap iterations[9]. The null hypothesis of no Granger causality is rejected when p-value are close to zero. Table-4 shows that only HPC and WoEC Granger cause IP given that their LR statistics are significant at 1% and 5% while their p-values are close to zero. For rest of cases, the neutral effect is present. Furthermore, IP does not lead renewable energy sources in all the cases. These results are almost coincident with those previously revealed by the wavelet approaches since a weak bivariate relationship was found between IP-renewable energy sources. The absence of lead/lag effects already confirm the intuition that increase in renewable energy in US will not exerts any harmful impact on environment thus economic development will not cause any serious threat on renewable energy resources.

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[9] The rolling window MWALD causality test procedure initially estimates the MWALD statistics for a predefined beginning sub-sample. For next estimation, the first (next) observation is removed (added) from the beginning (end) of the initial sub-sample. The relationship is subsequently re-estimated. In this study we estimate MWALD statistics using a sub-sample of 50, 60 and 70 months are used in this study. So if T=50, the first MWALD causality test statistics are obtained using a sub-sample period from January 1981 (start of our study period) to February 1985 (i.e. T= 50 observations). Then the second test statistic is obtained by using data from February 1981 to March 1985. This rolling procedure continues until the last observation is employed to examine for the causal relationship. This procedure is repeated for T=60 and T=70 to ensure the robustness of estimates, although we use 2000 bootstraps, under different estimation sub-sample.

Knowing that renewable energy sources are considered as alternative potential substitutes to traditional energy sources, we may expect that the increase of industrial production level will not require the use of these alternative resources (reserves). To better validate the aforementioned intuitive results, it is crucial to take into account the plausible occurrence of time varying abrupt changes that may drive the behavior of IP-renewable energy. We mean that their linkages may be subject to significant shadow changes that are unobservable by using a static approach that's why we further estimated a rolling window MWALD test over the sample period.

Table-4: Full sample bootstrap Granger causality tests

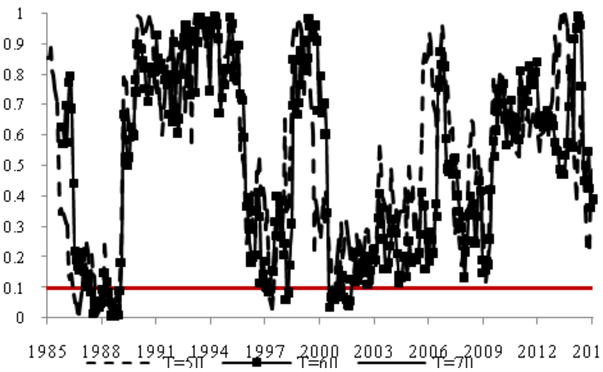
	LR-statistic	Bootstrap p-value		LR-statistic	Bootstrap p-value
$HPC_t \not\rightarrow IPI_t$	11.374**	0.0160	$IPI_t \not\rightarrow HPC_t$	3.3420	0.4700
$GEC_t \not\rightarrow IPI_t$	7.2877	0.1500	$IPI_t \not\rightarrow GEC_t$	7.5195	0.1440
$WoEC_t \not\rightarrow IPI_t$	30.997***	0.0000	$IPI_t \not\rightarrow WoEC_t$	4.0537	0.3840
$WaEC_t \not\rightarrow IPI_t$	2.7595	0.6100	$IPI_t \not\rightarrow WaEC_t$	6.6125	0.2160
$BioFC_t \not\rightarrow IPI_t$	7.1567	0.1580	$IPI_t \not\rightarrow BioFC_t$	5.3690	0.3520
$TBEC_t \not\rightarrow IPI_t$	2.9280	0.6240	$IPI_t \not\rightarrow TBEC_t$	3.4328	0.4740
$TREC_t \not\rightarrow IPI_t$	3.1725	0.4320	$IPI_t \not\rightarrow TREC_t$	3.5808	0.4900

Note: p-value is calculated using 2000 bootstrap repetitions. *, ** & *** denote significance at 10%, 5% and 1% level, respectively.

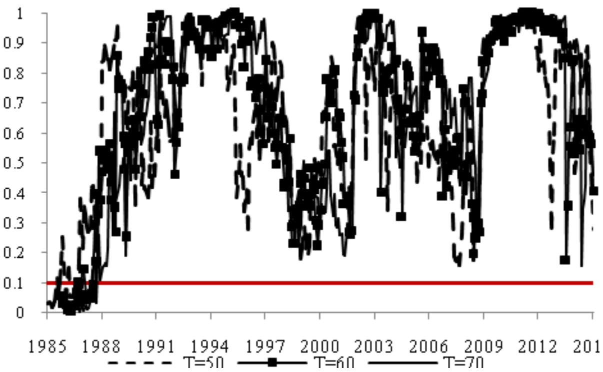
It is argued by Tang *et al.* (2015) that causal relationship may be unstable owing to frequent changes in the global economic environment. The causality test using the entire sample period is no sufficiently powerfull to reflect such changes. It is an inaccurate measure for the IP-renewble energy interplays since it is possible that a causal relationship exists in certain periods but does not exist in other periods. More precisley, we considered three long run windiw size (T = 50, 60 and 70 months) to adequaly captures any plausible causality effects in both directions. Figure-12 shows the unidirectional time varying causality running from renewable energy consumption (each series) to IP and vice versa i.e. feedback effect. The red horizental line indciate the 10% level of significance while vertical axis reflects the p-values between 0 and 1 thus when the rolling causality curves flucutuale below this line which means that a significant causality is detected. Upper are the causality amplitudes; higher is the probability of no causal links. A close look to Figure-12 reveals a great instability of both causality directions as the amplitudes varied widely over the whole period regardless of the window size. Interestingly, there are much more significant peaks when HPC lead IP since i.e. numerous successive boom and busts are depicted the red lines implying the abrupt changes in the causality pattern. Three causality peaks are located under 10% level of significance and they perfectly coincident with the occurrence of well known extreme events: the first high causality attraction corresponds to the occurrence of 1989-1990 crisis period, the second major causality interplays is coincident with 1997 Asian currency crisis and the last peak is located around 2000-2001 period which was marked by two extreme events in the US history (the dot-cum bubble followed by 2001 terrorist attack). All the mentioned periods of turmoil seem to have an impact on causality between IP and renewable energy consumption (each series) thus when the US economy was affected by these crises, industrial production process was much more dependent on renewable energy sources as source of economic safety. The IP plays the leading role during 1985-1988 period, marked by significant causal links while the remaining period is characterized by higher and insignificant causality fluctuations.

The unidirectional causality running from GEC to IP varies suddenly over the whole period with common trend regardless of the rolling window size. Almost all the fluctuations are located above the red line when the IP is the leader excepting two peaks that coincide with 2005-2006 and 2012-2015 periods. The inverted causality time path exhibits significant oscillations with long lasting duration at particular crisis times, firstly in 1988, than the longest duration is found for 1996-2009 period and the last one happened recently in fall of 2014. Obviously, GEC plays a leading role to stimulate IP over 13 years testifying the continuum of dependence between the US economic production and consumption of geothermal energy. In others words, we may conclude that GEC is a corner stone of the US industry that ensures its continuity. The visual inspection of Figure-12 proves that WoEC significantly leads IP in the aftermath of the global financial crisis (between 2009 and 2012) when the US experienced her biggest historical downturn thus the US economy was more consuming renewable energy sources to guarantee a minimum of safety of its global economy. IP leads WoEC over short lived period located in 1985-1986 and between 2001-2003 periods. IP similarly leads BioFC and WaEC (the reciprocal hypothesis is also valid) given that the significant causality amplitudes are located at the same dates of extreme events i.e. over the period of 1985-1988, followed by the 1995-1997 and 2009 as well as 2012-2015 periods respectively. These results imply a significant impact of these crises that induced a rising consumption of the two mentioned energy sources to boost the US industrial production.

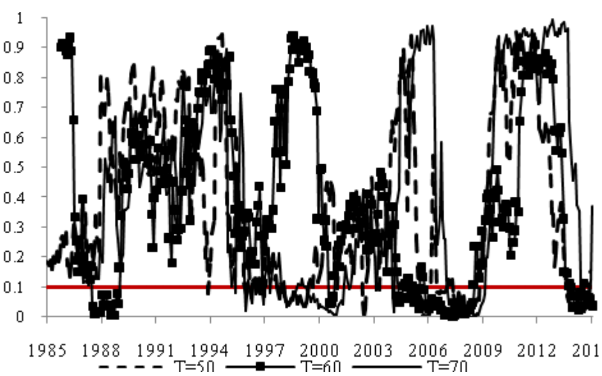
a) $HPC_t -/\rightarrow IPI_t$



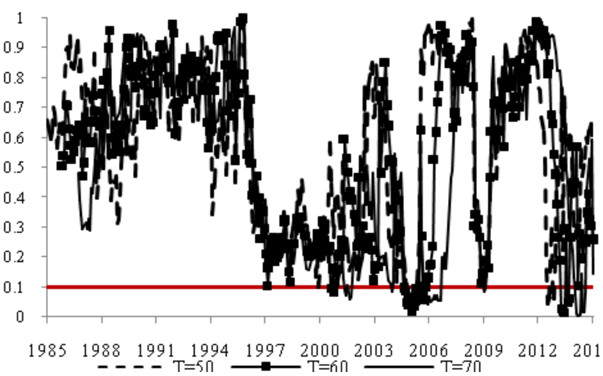
$IPI_t -/\rightarrow HPC_t$



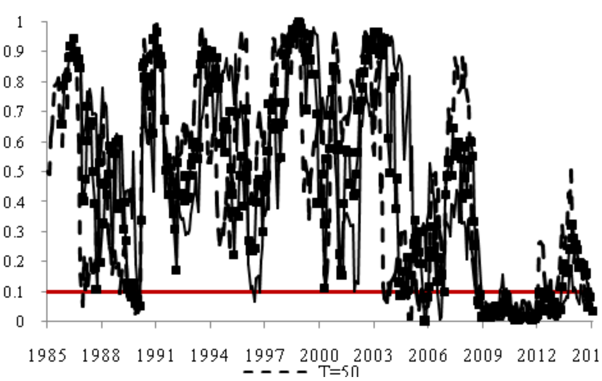
b) $GEC_t -/\rightarrow IPI_t$



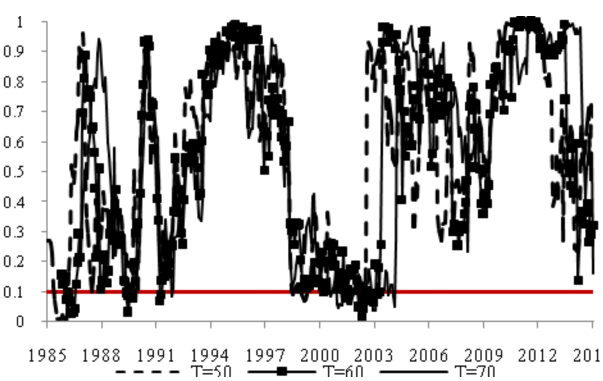
$IPI_t -/\rightarrow GEC_t$



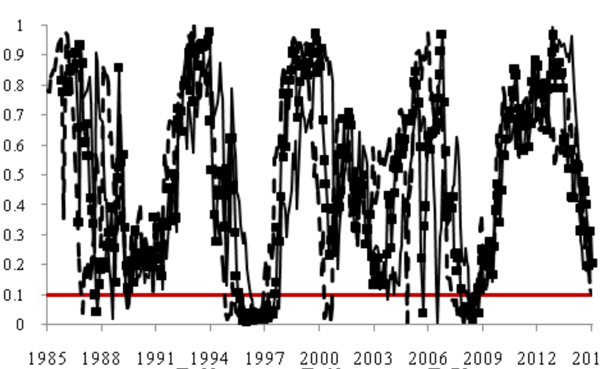
c) $WoEC_t -/\rightarrow IPI_t$



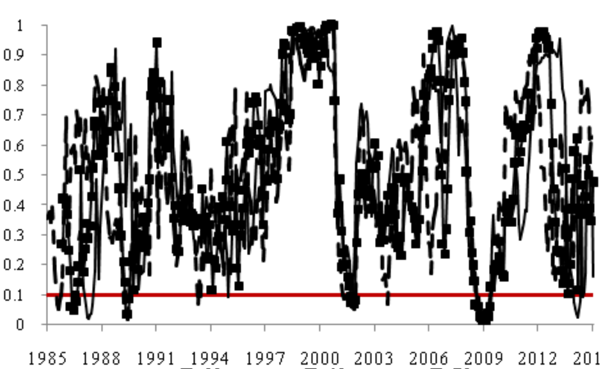
$IPI_t -/\rightarrow WoEC_t$



d) $WaEC_t -/\rightarrow IPI_t$



$IPI_t -/\rightarrow WaEC_t$



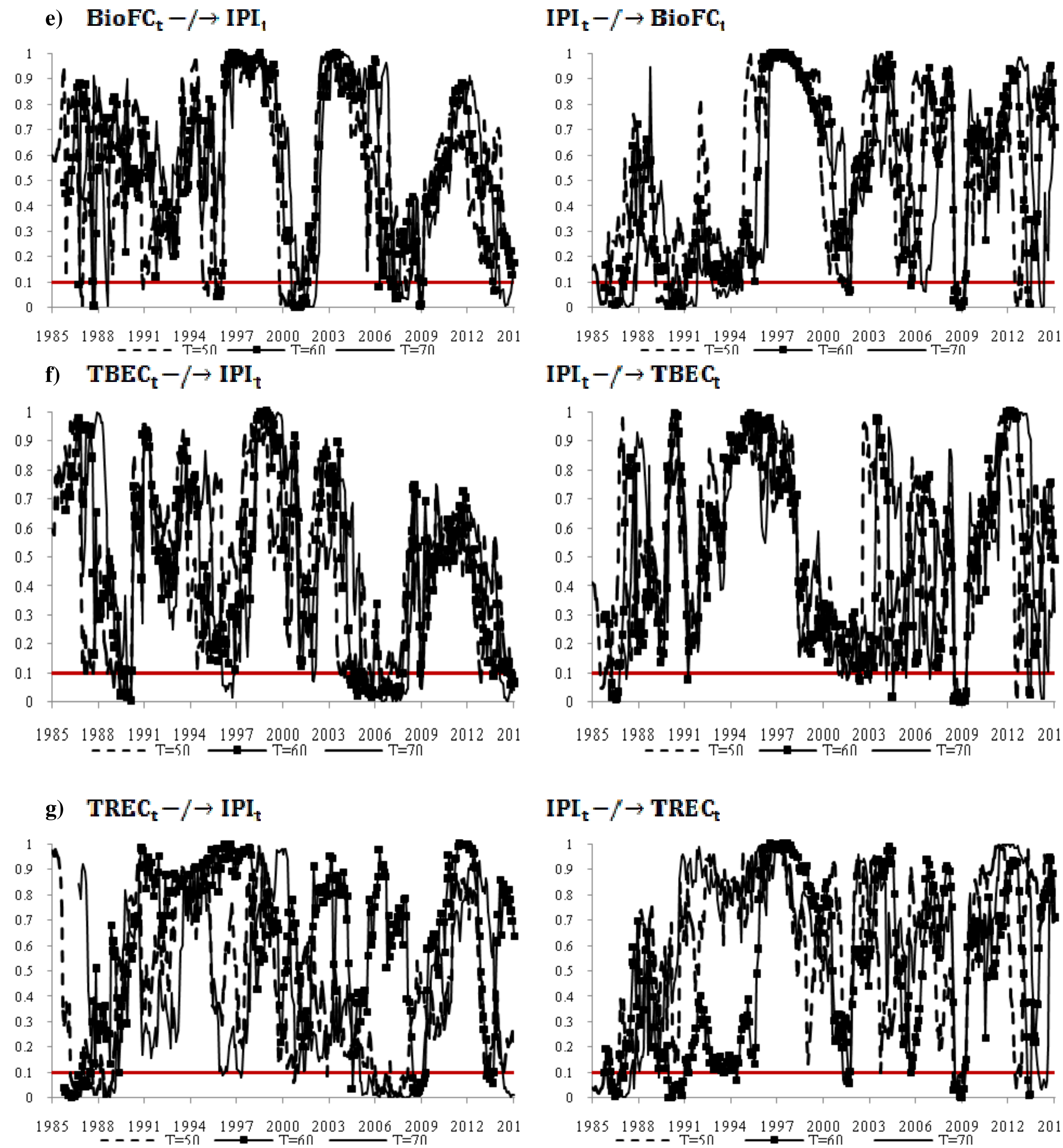


Figure-12: The Results of Bootstrapped Rolling MWALD Causality Test

5. Conclusion and Policy Implications

In this paper, we examined dynamic linkages between economic activity and renewable energy sources in U.S. The monthly data for the period of January 1981 to March 2015 is used for continuous wavelet (CWT) namely wavelet transform (WT), wavelet squared coherence (WTC), wavelet multiple coherence (WMC). The results of discrete wavelet analysis i.e. wavelet correlation and wavelet cross-correlation reinforce the CWT analysis. To capture different regime present in IP-renewable energy nexus, we finally investigate this link through full sample MWALD and bootstrap rolling window MWALD test using TY framework.

Both wavelet and rolling Wald test approaches highlighted the particular period of times where the US production and renewable energy sources exhibited significant interplays despite their diversity thus to ensure the continuum of the global economic prosperity, all sources should be taken into account, therefore the combination of all these renewable energy resources is undoubtedly the credible economic engine that will protect against any barriers that may curtail economic development. The policy makers should carefully think on the best and efficient strategies to optimize the allocation of the given resources. Given the casual nexus at 10% of significance regardless of the causality direction, the rolling MWALD test corroborates the previous findings established through wavelet between IP-renewable energy pairs and the existence of possible positive relationship across time horizon and especially in the long run. The results and findings of this study are in line with the important information's provided by the 2014 EIR report dealing with the US renewable energy sources. This latter underlined the importance of total energy consumption in USA during 2014 for what 9.8% belongs to mixed renewable energies. The given report also mentioned that the highest consumed resources were the hydropower, biomass wood and biomass fuel as proven by the rolling test results.

Moreover, the findings of this work are convergent with those of Bilgili *et al*. (2015) as they similarly confirmed the co-dominance of positive /negative correlation between the US industrial production and renewable energy sources. The authors found significant sub periods of high attractions including 1988-1989, 1989-1991, 1995-1997, 2000-2003 and 2005-2008 periods respectively when either energy consumption or IP played the leading role. By using the partial wavelet coherence they also reached similar conclusions with reference to the periods of highest co-movement patterns. Given the striking similarities between the three approaches applied in this paper and the convergence within the recent empirical finding in this research fields, the US policy makers may orient their energy policies to the adoption of the rules that may guarantee sustainable development: growing consumption of renewable energy sources through time (expected increase by a rate of 2.5% per year until 2040 according to the EIA) will push the policy authorities to follow demand side management strategies for renewable energies to further boost the customer services in consumption of energy (Ardakani *et al*. 2014, Biglili *et al*. 2015). The effectiveness of such measures requires making most renewable energy sources competitive despite that the amount of energy in a given amount of raw biomass tends to be significantly less through time thus police makers are encouraged to also account on the non renewable DSM strategies to reduce the exploitation pressure on the renewable energy resources. Another reasonable solutions are the resorts to subsidies for low emitting renewables that will eventually, increase welfare (economic growth) together with an increase in environ- mental efficiency (during economic growth). According to the recent IRE report (2014), some of today's more promising processes for tapping renewable energy involve using chemical or thermal conversion in an attempt to mimic the results of a long lasting process that create rich energy fossil fuel from biomass. In other words, we may conclude that the US overall continuum of economic growth is conditional on optimal diversification/mix of renewable energy resources for what some relevant policy measures need to be established in a way to harmonize between the government assistance (subsidies) and the new advanced technologies.

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