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ARTICLE

On the interactions among environmental degradation, energy consumption and economic growth: a time–frequency analysis using wavelets

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ABSTRACT
This paper aims to investigate the interactions between CO_2 emissions, economic growth and energy consumption in India for 1970–2017 within the time–frequency domain using wavelet techniques. The results show that the interaction between energy consumption and CO_2 emissions is strong and varies significantly across time–frequency bands, indicating that the energy consumption leads to environmental degradation. The negative effect of economic growth on CO_2 emissions is only statistically significant in the short run. In addition, the findings reveal a positive association between economic growth and energy consumption across time–frequency bands, demonstrating energy consumption increases economic growth, which in turn heightens the CO_2 emissions. There should be improved energy use and reduced CO_2 emissions.

KEYWORDS
Emissions; Kuznets; wavelet; energy; economy; causality

Introduction

An increase in greenhouse gases leads to global heating. The Word Bank notes that carbon dioxide accounts for 58.8% of these gases [1]. Soytas and Sari [2] recognise that human activities have greatly contributed. More than 80% of the existing world energy demand derives from fossil fuels [3]. World action is necessary to achieve zero or low-carbon growth. India is the fourth largest contributor to GHG (approximately 5% of overall GHG emissions) and its CO_2 emissions rose by 5.2% between 1990 and 2009 (based on the compound annual growth rate) [4]. In India, more than 68% of electricity is produced by coal, which is a major source of CO_2 emissions (58% of GHG emissions come from the energy industry and more than 65% of which is generated by electricity) [5]. India's energy output in 2013–2014 was dominated by coal and lignite with a share of 73.48% of overall production, followed by 11.81% of crude oil and 10.18% of natural gas. India is one of the world's fastest growing emerging economies and the world's second most populated country with over one billion inhabitants, suggesting that in the coming decades, its energy demand and CO_2 emissions will continue to increase in the age of globalisation [6].

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Kraft and Kraft studied the relation between energy and GNP in 1978 [7], and many other researchers have encountered the same facts in many developed and developing economies. Taking ASEAN nations such as Indonesia, Malaysia, Thailand, Philippines and Singapore as an example, Azam et al. [8] revealed that energy use had a statistically significant long-run linkage to economic growth. Pao and Tsai [9] and Sebri and Ben-Salha [10] have explored the nexus of economic growth, energy use and carbon dioxide emissions in BRICS nations; Salahuddin and Gow [11] and Kayıkçı and Bildirici [12], in respect to GCC nations; Kayıkçı and Bildirici, Al-mulali et al. and Arouri et al. [12–14], in respect to MENA nations; Apergis and Payne [15] and Saboori et al. [16] in respect to OECD countries; Al-Mulali and Sab [17] in relation to SSA countries; Saboori and Sulaima [18] with respect to ASEAN nations, Liddle and Lung [19]; Al-mulali et al. [13] in relation to Latin America and Caribbean; Xue et al. [20], with respect to developed nations; Liddle and Lung [19], with respect to both developed and less developed nations and Hossain [21] in relation to newly industrialised nations.

Most of these researches scrutinised the causal nexus among energy use, carbon dioxide emissions and economic growth employing panel co-integration approaches such as Granger causality tests, panel unit root and panel co-integration [22]. The empirical results of such studies have made it possible for researchers to decide whether causality is from carbon dioxide emissions to economic development or vice versa. The EKC hypothesis was validated by some of these studies, resulting in an inverted U-shape relationship between economic growth and carbon dioxide emissions. Others have confirmed the relationship to be in the form of a linear shape, S shape, N shape, and a variety of other shapes. These researchers have implemented a variety of strategies to enhance a sustainable nexus between economic growth and carbon dioxide emissions in the quest of attaining economic growth without compromising the environmental quality.

Other studies have scrutinised the relationship between the energy use, economic growth and carbon dioxide emissions for specific nations. Using Chile as an example, Joo and Yoo [23] investigated this nexus and found a set of unidirectional causal linkages running from carbon dioxide emissions to economic growth, energy use to economic growth and finally from energy use to carbon dioxide emissions. But, Joo et al. [23] did not find any evidence of unidirectional causal linkages from economic growth to energy use, from economic growth to carbon dioxide emissions, or from carbon dioxide emissions to energy use. These authors established that the causality can run from energy use to economic development but not the other way round, in the Chilean setting.

Using the co-integration test approach by Johansen [24], Yavuz [25] has located a long-run nexus among per capita carbon dioxide emissions, per capita income and per capita energy use, in the Turkish context. In relation to Nepal, Bastola and Sapkota [26] concluded a long-run one-way causality running from energy use to carbon dioxide emissions and vice versa and one-way causality running from economic growth to both carbon dioxide discharges and energy use. Yang and Zhao [27], studying India, employed directed acyclic charts and identified a unidirectional

Granger causality running from energy use to carbon dioxide releases and economic development, and a two-way causation between carbon dioxide secretions and economic growth.

Furthermore, Hwang and Yoo [28] concluded that a bidirectional causal relationship exists between carbon dioxide releases and energy use in Indonesia. In addition, Menyah and Wolde-Rufae [29] in the United States of America, Zhang and Cheng [30], Chang [31], Fei et al. [32], Zhang et al. [33] and Hu et al. [34] in China, Shahbaz et al. [35] in Indonesia, and Alkhathlan and Javid [36] in the Kingdom of Saudi Arabia have undertaken similar research. In most of these research, the EKC hypothesis was validated, revealing an inverted U-shaped nexus between economic growth and carbon dioxide discharges. These research studies show that an increase in economic growth will promote environmental quality through reduced emissions. Environmental damage rises with the surge of output until a threshold is achieved then it commences to drop, emissions fall, environmental quality is achieved.

The current literature is not conclusive. Although some studies have established a two-way causality between economic growth, energy use and carbon dioxide, others have failed to do this and also failed to identify a one-way causation running from one variable to another. Although the nexus among energy consumption, economic growth and CO_2 emissions has been investigated extensively, the results have been inconclusive and conflicting. According to Odugbesan and Rjoub [37], these conflicting and unreliable results could be avoided if the author can deploy a novel technique. These studies have deployed standard time series techniques which assume that the economic series have only two time scales, namely short-run and long-run equilibrium dynamic relationship [38–40]. Therefore, the nexus between economic growth, energy use and CO_2 emissions at different time horizons (scales) or frequencies has not yet been sufficiently studied.

In this regard, wavelet-based techniques seem to be a very promising and innovative approach as it takes into account both time and frequency domains simultaneously. Accordingly, this paper employs wavelet analysis that can investigate the interrelationship between economic growth, energy consumption and carbon dioxide emissions at different time horizons (scales). The advantage of employing wavelet-based techniques over the conventional times series techniques is that additional scales corresponding to time can be augmented. This allows to be seen patterns of relationships at different scales in the frequency domain coupled with time domain that would be otherwise difficult to capture when conventional time series models are applied [41, 42]. The wavelet technique reflects flexibility, which provides a unique opportunity to detect the dynamics of relations between the energy consumption, economic growth and carbon dioxide emissions over time and across different time horizons (scales), offering a wider picture than traditional time domain models, combining all scales together.

Linkages between carbon dioxide, economic growth and energy consumption at different scales or horizons have been under researched. Furthermore, the wavelet-based approach specially the wavelet coherence can simultaneously examine the relationship and causality between carbon emissions, economic growth and energy consumption at different frequencies and time periods. To the best of our knowledge, no study has previously employed the wavelet tools such as wavelet power spectrum, cross-spectrum wavelet, wavelet coherence and phase difference to investigate the dynamic relationship and/or causality among economic growth, energy consumption and CO_2 emissions at different scales or horizons in India. Our study focuses on this identified gap.

The rest of the paper is structured as follows: Section 2 provides data and methodology. Section 3 discusses empirical results and discussion. Section 4 presents concluding remarks and policy implications.

Data and methodology

Empirical model

The existing literature indicates that CO_2 emissions are mainly driven by economic growth [43]. Following Dong et al. [43], we specify the dynamic linkage between economic growth and CO_2 emissions in India as follows:

$$\ln CE_t = \alpha + \beta_1 \ln GDP_t + \varepsilon_t \tag{1}$$

where CE represents per capita CO_2 emissions and GDP denotes per capita gross domestic product. Wang et al. [44] suggest that energy consumption will increase environmental pollutants. Thus, this study extends Equation (1) by adding the energy consumption as an independent variable to investigate its dynamic effects on CO_2 emissions in India and the specification is as follows:

$$\ln CE_t = \alpha + \beta_1 \ln GDP_t + \beta_2 \ln EC + \varepsilon_t \tag{2}$$

where α is the intercept term, β and β_2 are the parameters and ε_t is the residual term. EC denotes per capital energy consumption, GDP denotes per capita gross domestic product and *t*, which is subscript, indicates time series.

Wavelet model

In this section, we briefly describe the usefulness of the wavelet methodology in identifying the relations between series based on time and frequency domains. The wavelet methodology is a very powerful mathematical method designed for signal processing in the time–frequency domains and provides an opportunity to capture simultaneously the dynamics of time-scale behaviour of economic series. The wavelet method, originating in 1980, is superior to the popular Fourier analysis.[1] The wavelet model combines the information derived from both time dimension and frequency dimension. It maintains the time information which is, thus, appropriate for explaining the non-stationary time series behaviour. Moreover, the wavelet-based tool has an advantage over standard time series models which allow drawing dynamic relationships between economic series for a set of only two scales under the assumption that estimates have short-term and long-term equilibrium relationships.

Therefore, to demonstrate how the local variance and covariance of the pairwise interactions between carbon dioxide, economic growth and energy consumption evolve, this paper employs continuous wavelets and cross-wavelet transform, and cross-wavelet coherence and phase analysis to measure local dynamic dependence between aforementioned series in the frequency domain.

Continuous wavelet transform

The continuous wavelet transform, which reflects the analysis on the temporal evolution of given time series, is defined as

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

where $W_x(u,s)$ denotes a mother wavelet obtained by a family of wavelet daughters which result from convolving signals, u represents the translation parameter which reflects the time domain function, s denotes the dilation parameter (scale) which determines the wavelet width and frequency resolution and the asterisk represents the complex conjugate. Furthermore, CWT characterises decomposition and reconstruction, which consequently offers the following function

$$x(t) = \frac{1}{C_\psi}\int_0^{\infty}\left[\int W_x(u,s)\psi_{u,s}(t)du\right]\frac{ds}{s^2} \quad s>0 \tag{4}$$

More so, the continuous wavelet transform manifests capacity to preserve energy levels of the time series variables. This characterises power spectrum analysis, which identifies the variance of the power spectrum and is specified as

$$\|x^2\| = \frac{1}{C_\psi}\int_0^{\infty}\left[\int |W_x(u,s)|^2 du\right]\frac{ds}{s^2} \quad s>0 \tag{5}$$

Wavelet power spectrum

In a univariate analysis, the wavelet power spectrum is defined as square of modulus of continuous wavelet transform. As pointed out by Torrence and Compo [45] and Aguiar-Conraria et al. [46], the wavelet power spectrum captures the local variance by measuring the relative contribution of each time and each scale to variance of time series variables. Therefore, the wavelet power spectrum shows the energy density of a signal in time–frequency space or areas where pair series have high common power. Grinsted et al. [47] point out that the wavelet power spectrum needs to be tested; the conjuncture states that the wavelet power spectrum of variable of interest is statistically significant. The wavelet power spectrum can be specified as follows:

$$D\left[\frac{|W_x^n(s)|^2}{\sigma_x{}^2} < P\right] \Rightarrow \frac{1}{2}P_f\chi_v{}^2 \tag{6}$$

where P_f is the mean of the power spectrum with frequency f.

Cross-wavelet power and wavelet squared coherence

Three different approaches can be applied to identify the dependence between two time series in the time and frequency domains: cross-wavelet power, wavelet power spectrum (WPS) and cross-wavelet transform [48]. The WPS measures the variance of a single wavelet, which detects and measures relations between two time series; the cross-wavelet power assesses the covariance of the time series and the CWT can control the dependencies of frequency and time between two time series. Aguiar-Conraria et al. [46] define wavelet coherence (WTC) 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 frequency and in time), between two-time series'. Wavelet coherence is expressed as the coefficient of the correlation of time–frequency space. We define wavelet coherence as follows:

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

where R^2 represents wavelet coherence and S is a smoothing operator. Interestingly, the value of wavelet coherence ranges from 0 to 1. It is a localised correlation coefficient in time–frequency space and is a useful technique for analysing co-movements across two time series. Wavelet coherence can be interpreted similarly to the correlation coefficient, suggesting strong dependence when the value is close to 1 and weak dependence when the value is close to 0. Likewise, the WPS explains the variance of a time series and covariance, which captures cross- wavelet power between two time series at each scale or frequency. If the variance of a time series becomes large, the wavelet suggests the existence of a sizeable power spectrum. The statistical significance of the wavelet coherence coefficient is estimated using a Monte Carlo simulation, but little is known about its theoretical contribution [44].

Phase pattern

A phase difference is expressed as the complete cycle of the time series for a function of frequency, giving us information about a delay on or synchronisation between the two time series. In addition, it captures the positive and negative associations and lead–lag relations between two time series in a time–frequency dimension. According to Torrence and Webster [49], the wavelet coherence phase difference is defined as follows:

$$\phi_{xy}(s) = \arctan\left(\frac{\Im\left(\left(s^{-1}W_n^{XY}(s)\right)\right)}{\Re\left(\left(s^{-1}W_n^{XY}(s)\right)\right)}\right) \tag{8}$$

where $\Im$ and $\Re$ denote the imaginary and real component parts of the smooth power spectrum, respectively. The coherence phase uses arrows, showing the relationship between the two time series: (1) When the arrows point to the right (left), the series show in-phase (out-of-phase), and the correlation coefficient is positive (negative) and (2) when the arrows point down (up) the second (first) variable leads the first (second) variable by a 90° angle. Further, when the phase difference tends towards zero, it suggests that the variables move together at a given time–frequency.

Data sources and pre-analysis

The paper uses annual data covering 1970–2017, and the variables in the study contain CO_2 emissions, energy consumption and economic growth. The measure of CO_2 emissions employed in this study is metric tons per capita. The measures of energy

Table 1. Variable definition & metrics & source.

Variables	Description	Source
CO_2	Per capita Carbon Dioxide Emissions (Million tonnes of carbon dioxide)	BP Statistical Review of World Energy 2018
EC	Per capita Primary Energy Consumption (Million tonnes of oil equivalent)	BP Statistical Review of World Energy 2018
GDP	GDP per capita (constant 2010 US$)	World Development Indicators

Table 2. Descriptive statistics.

Variable	$\ln CO_2$	lnGDP	lnEC
Mean	2.830	2.822	2.344
S.D.	0.327	0.231	0.325
Min	2.279	2.546	1.812
Max	3.370	3.293	2.877
Skewness	−0.0218	0.5544	−0.02475
Kurtosis	1.7882	2.0339	1.7785
IQR	1.2773	0.9085	1.2651
JB	2.9407	4.3254	2.9888
Probability	0.2298	0.115012	0.2244

$\ln CO_2$ represents CO_2 emissions, lnGDP is the economic growth and lnEC is energy consumption. S.D. denotes standard deviation.

consumption and economic growth are tonnes of oil equivalent per capita and per capita GDP, respectively. The data on CO_2 emissions, economic growth and energy consumption are collected from BP Statistical Review of World Energy 2018 [50] and World Development Indicators [51] (Table 1).

Table 2 summarises the descriptive statistics on the interactions between CO_2 emissions, energy consumption and economic growth. We show that CO_2 emissions have the highest mean value of 2.830% and range between a maximum of 3.370% and a minimum of 2.279% for 1970–2016 followed by economic growth. Based on the skewness, all variables confirm to normality. Furthermore, using Jarque–Bera (JB) probability, Table 2 reveals that all variables confirm to normality.

Empirical results and discussion

This section reports the results of wavelet analysis used to assess the interactions between CO_2 emissions, energy consumption and economic growth in India. In the empirical results, we mainly conduct the analysis through wavelet power spectrum, cross-wavelet power and wavelet coherence and phase differences.

Wavelet power spectrum analysis

Generally speaking, wavelet power spectrum (WPS, hereafter) analysis is a tool that measures the local variance of underlying variables and it also assesses the behaviour of economic series in the time–frequency domains. Before analysing the interactions between CO_2 emissions, energy consumption and economic growth in India, the contour plots designed to visualise WPS require a close look because these plots disclose interesting conclusions. The WPS plots encompass period, time and power. The horizontal axis represents time in years 1970–2018, whereas the vertical axis denotes the period. The vertical axis is mainly decomposed to 8 levels, which range from high to low frequencies corresponding to short-, medium- and long-run dynamics. Since annual data is used in the paper, based on levels we set three scales that show variations within 2 years, such as 1–2 years (scale 1), 4–8 years (scale 2) and 8–16 years (scale 3). Based on local variance, regions with red colour denote very high intensity levels of WPS and regions with blue colour reveal low intensity levels of WPS. The intensity of WPS increases from blue areas to red areas. Moreover, WPS requires the researcher to check whether WPS is statistically significant against null hypothesis of a stationary process with a background power spectrum. The black contour line restricts the cone of influence (COI), which represents 5% significance level, as estimated from Monte Carlo simulations. Given the black contour line, the values inside conical contour are interpreted as dynamic patterns that are statistically significant at 95%. Values outside this cone are out of consideration.

The graphs shown in Figure 1(a–c) reveal that WPS does not show resemblances over time and across frequencies. The plots show moderate WPS values for CO_2 emissions, energy consumption and economic growth. The CO_2 emissions present short-run dynamics at the higher frequencies and range from 2 to 4 years' time scale over the

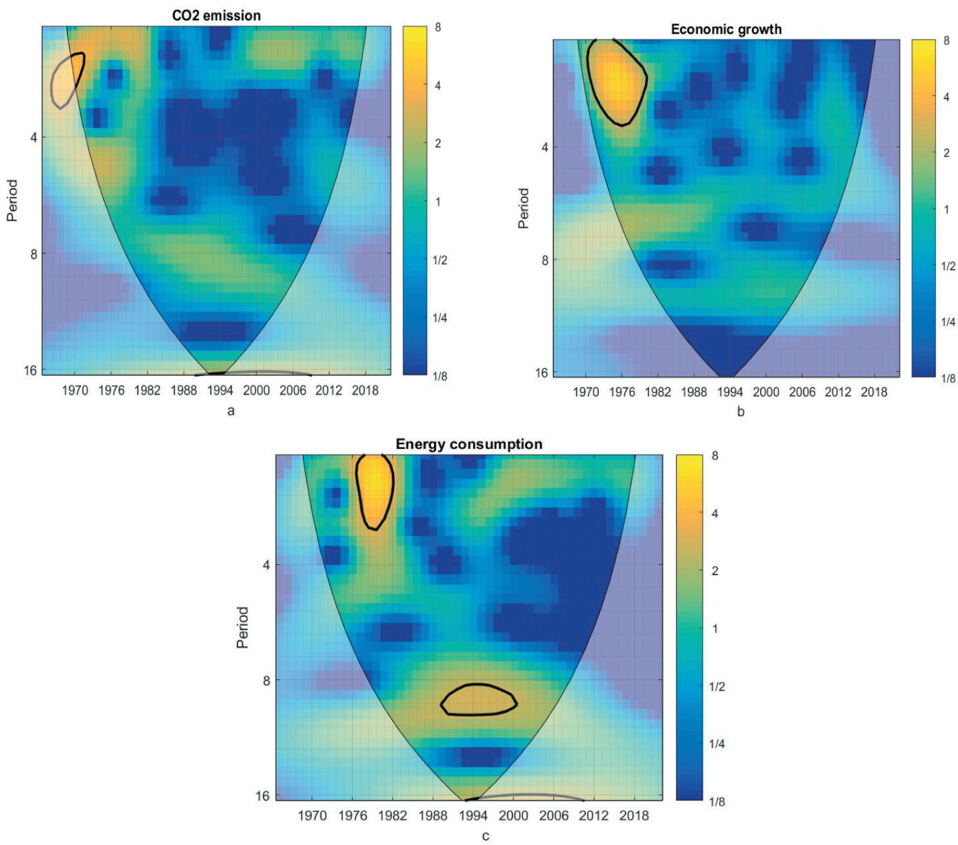

Figure 1. The continuous WPS of CO_2 emissions, energy consumption and economic growth based on annual data from 1970 to 2017. Note: The thick curve represents cone of influence (COI) with 5% significance level. The blue contour denotes low power.

1970–1982 period, suggesting that WPS of CO_2 emissions is driven by spikes and drifts. Similarly, the energy consumption and economic growth exhibit the moderate power at short to long scales corresponding to frequencies between 2–4 years and 8–10 years, coinciding with periods 1970–1982 and 1988–2000 periods, respectively. Moreover, the Islands with the highest WPS are found at time scales 2–4 years and 8–10 years. The existence of these regions implies that the CO_2 emissions, energy consumption and economic growth which tend to concentrate at periods 1970–1972, 1971–1980, 1976–1980 and 1981–2001 demonstrate vicissitudes.

The wavelet power spectrum (WPS) underlying the dynamics of CO_2 emissions, energy consumption and economic growth reveal that significant variations are mainly concentrated to 2–4 years where red yellow vortices sharply disappear at lower frequencies. The aforementioned abrupt changes seem to disappear over 5 years except energy consumption because all series are characterised by no power at middle and low horizons. Taken together, the empirical evidence regarding localised variance of CO_2 emissions, energy consumption and economic growth indicates that they present short- and long-run dynamics.

Cross-wavelet power spectrum analysis

The cross-wavelet power spectrum (CWPS henceforth) gives us a measure of a local covariance between two financial series in time–frequency domains [46]. CWPS reflects localised covariance between CO_2 emissions, energy consumption and economic growth. Figure 2(a–c) presents CWPS results suggesting that, for example, the relationship between CO_2 emissions and economic growth is more influenced by long-run dynamics as shown in Figure 2(a). We observe two yellow regions coinciding with periods 1994–2006 and 2007–2010 and these regions identify the existence of significant covariance corresponding to low and high frequencies. Specifically, the first area reveals that covariance between CO_2 emissions and economic growth is statistically significant and that longer scales (5–6 years) about 2007–2010 are identified to notify strong covariance of the variables under consideration, indicating that the recent global financial crisis has had substantial impact on the association between CO_2 emissions and economic growth. In doing so, the covariance gradually decreases at all scales in the latter years of sample (2011–2017).

The second region indicates that the influence of CO_2 emissions on economic growth appears to be strong at low frequencies during the period 1994–2006. Moreover, the arrows generally reflect a relative phasing of paired series. In the former region, CO_2 emissions and economic growth are anti-phase, which implies that CO_2 emissions lead to economic growth. The arrows suggest that an increase in CO_2 emissions is followed by an increase in economic growth or economic growth is lagging behind CO_2 emissions because the arrows that point right (left) measure in-phase and anti-phase relationships of pairs considered. For instance, the arrows that point straight down suggest that the variable in the right-hand side of equation leads the variable in left-hand side, and arrows that point straight up mean that the series on the left-hand side leads the series on the right-hand side. On the contrary, the latter region indicates that CO_2 emissions and economic growth are in-phase, which means that CO_2 emissions lag behind economic growth.

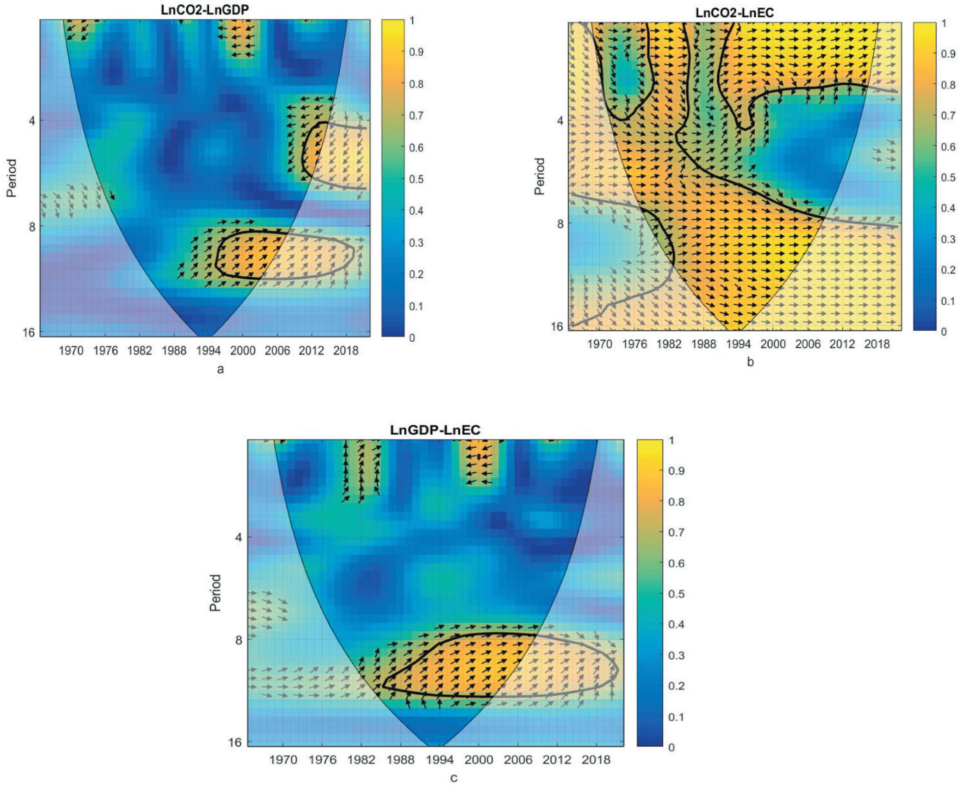

Figure 2. The cross-wavelet power spectrum between CO_2 emissions, energy consumption and economic growth based on annual data from 1970 to 2017.

Figure 2(b) shows the CWPS between CO_2 emissions and energy consumption. The CWPS gradually increases from high frequency to low frequency during the periods ranging from 1970 to 2017. It is notable that CWPS with scales of 1 to 4 and 7 to 10 years which belong to 1970–1976 and 1976–1982, respectively, exhibit the existence of strong covariance in the pair considered. Specifically, there are common features where CWPS of two series is high and statistically significant. Furthermore, Figure 2(c) reveals that the covariance between energy consumption and economic growth has strong and significant power over 1985–2006 for 8–12 years of scale (at low frequency and long term). Taken together, the plots regarding CWPS display features that represent high (significant) powers of two series at different frequency–time dimensions. Nevertheless, CWPS is not the most expedient tool as it loses information inherent to phases because two series that involve similar significant-power areas may merely not be identical [52, 53]. In regard to this, the wavelet coherence and phase difference become the most suitable tools. As a novelty it captures the cause and effect relationship through frequency–time domains between CO_2 emissions, energy consumption and economic growth. In the subsequent section, the results of wavelet coherence and phase difference are discussed.

Wavelet coherence

Figure 3 shows the results of wavelet coherence between CO_2 emissions, energy consumption and economic growth. As noted above, the wavelet coherence (henceforth, WTC) is explained as the localised correlation for pairs of series in the time–frequency domain. WTC determines mainly the co-movements of each two series of interest across frequency–time space. The horizontal axis represents time, whereas the vertical axis depicts period. Just like wavelet power, the wavelet coherence is portrayed by shaded contours ranging from blue which symbolises no co-movements to yellow which identifies the existence of strongest co-movements. These shaded contours are estimated from the Monte Carlo simulation applying phase randomised surrogate series. The solid-curved line in these plots shows the areas where the WTC is statistically significant at 5% level of significance.

Beyond this curved line, caution regarding the interpretation of WTC must be applied, as the edge effects have substantial influences on WTC. The WTC does not only allow us to detect the interdependences as well as contagion[2] among variables under the study but also reveals their lead–lag relationships in frequency–time space [46]. Moreover, arrows use the phase difference tool to examine the causality relationships among the variables under this paper following the conventional literature [46, 54].

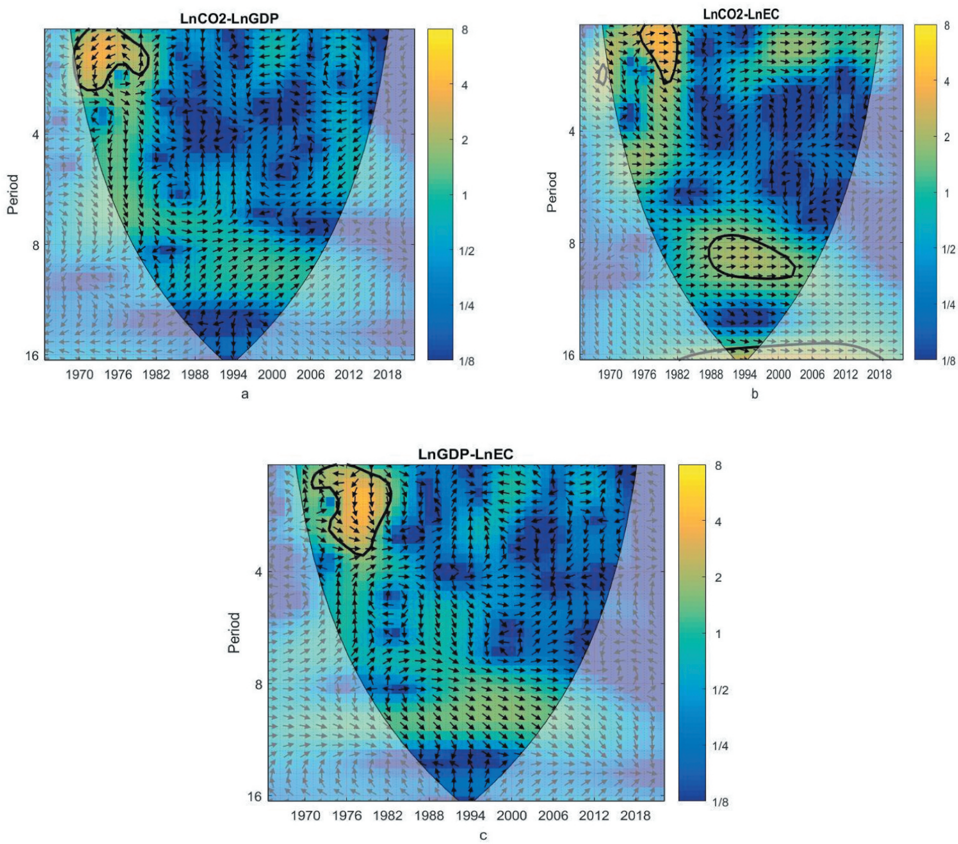

Figure 3. Wavelet coherence between CO_2 emissions, energy consumption and economic growth based on annual data from 1970 to 2017.

Phase difference is symbolised with the arrows which are pointed to right and left. For these arrows, the relationships between each pair variables are of in-phase and anti-phase, respectively. For the in-phase, arrows denote that the two series are positively related and tend to move together at a given frequency and time space. Arrows pointing right and up mean that second series (i.e. CO_2 emissions) leads the first series (i.e. energy consumption and economic growth). The energy consumption and economic growth lead CO_2 emissions if arrows point right and down. On the other hand, the arrows directed to left represent anti-phase and indicate negative relationships between each pair moving in opposite directions. The second variables like energy consumption and economic growth lead the first series, CO_2 emissions, when the arrows are oriented left and up. Otherwise CO_2 emissions lead when the arrows are oriented to left and down.

Figure 3(a) presents the wavelet coherence between CO_2 emissions and economic growth. We notice that wavelet coherence is statistically significant during 1970–1976 for high frequency domain in India, especially less than 4 years scale. Notably, the wavelet coherence exhibits a strong and negative relationship between CO_2 emissions and economic growth for India and indicates CO_2 emissions leading. The interaction between the two series appears to be more persistent in short-run dynamics and does not exist in periods longer than 3 years. This finding is not consistent with the known EKC relationship between CO_2 emission and economic growth.

This finding does not support the environmental Kuznets curve (EKC) hypothesis. Moreover, the finding supports the previous literature [55, 56]. This inconsistency is more likely to be attributed to econometric models because the previous studies were mainly restricted to the application of standard time series techniques. Corroborating the result of wavelet coherence, strong effects of economic growth on CO_2 emissions are found during 1970–1976, but the effects remain registered over short scale year. For the rest of period, no long-run relationship between the series is observed, implying that the neutrality hypothesis exists [57].

As for energy consumption, Figure 3(b) reveals that the energy consumption is strongly related to CO_2 emissions around 1976–1980 and 1988–2002, especially at high and low frequencies, respectively. The co-movement between CO_2 emissions and energy consumption shows positive and statistically significance at the 5% level at the two vortices (i.e. short- and long-run dynamics). Furthermore, the empirical evidence shows that the arrows of phase differences are almost right and up, indicating that the two series move cyclically and CO_2 emissions are leading energy consumption, which implies that an increase in CO_2 emissions is followed by more energy consumption. Nonetheless, it seems that the strongest interactive link between CO_2 emissions and energy consumption is detected during 1976–1980 over 1–2 years scale.

So in general, from 1988 to 2002, the impact of energy consumption on CO_2 emissions appears to be weak at low frequency (i.e. long term). The findings are consistent with previous work [58, 59].

Finally, Figure 3(c) presents the wavelet coherence graph between economic growth and energy consumption in India. Strong and significant co-movement between both series is found during 1973–1982 and 1982 and 2006. The vortices that are encircled by regions of yellow colours exhibit that energy consumption has substantial effect on economic growth and these areas correspond to scales of 1–3 years and 5–12 years. It is notable that the two variables appear to be positively correlated, although the regions have not the same effects. From medium- to long-run (i.e. 5–12 years scale), co-movements seem to increase gradually over time and frequency bands. The phase differences show that the two series are in phase as the arrows are oriented to right and down. In this case, energy consumption serves as leading series, implying that a rise of energy consumption increases the economic growth. The lead–lag relationship moves from energy consumption to economic growth, which in turn increases the CO_2 emissions. The results support the previous studies, which confirmed positive and significant unidirectional causality running from energy consumption to economic growth [60, 61].

Concluding remarks and policy implications

Standard econometric models often fail to model accurately interactive linkages of variables because of irregularities and complex structural changes in time series data. Accordingly, this paper uses wavelet techniques aiming to examine the dynamic interactions between CO_2 emissions, energy consumption and economic growth over different time–frequency domains for India, especially the time ranges from 1970 to 2017. The wavelet tools allow us to determine the lead–lag causal relationships between variables under consideration at different time horizons across the sample period. Our results suggest that the strength of the interactive link between CO_2 emissions and economic growth for India appears to vary significantly over time–frequency space. A negative and significant effect of economic growth on CO_2 emissions is found during 1970–1976, but this relationship only exists at high frequencies. The research reveals the presence of short-run causal association between the pair of interest.

Surprisingly, this finding does not support the Environmental Kuznets Curve Relationships (EKC hypothesis), which posits that higher income is mainly related to a rise in the rate of CO_2 emission but, after threshold, the higher income decreases the rate of environmental degradation for India. Moreover, strong and positive relationship between CO_2 emissions and energy consumption is concentrated at 1–2 and 8–10 years scale across the sample period. The impact of energy consumption on CO_2 emissions is more robust in a short run. Further, the phase difference indicates that the series are in phase and CO_2 emissions are leading energy consumption. An increase in the rate of environmental degradation for India drives substantially its energy consumption.

Finally, the co-movement between economic growth and energy consumption proves the existence of a positive and strong link between both series 1973–1982 and 1982 and 2006, corresponding to scales of 1–3 years and 5–12 years. The energy consumption serves as leading series because arrows are oriented to right and down. This means that the economic growth is responsive to a rise of energy consumption, which in turn increases the CO_2 emissions.

The implications support recommendations for policymakers in India. The top priority of policymakers is to make precise energy policies to control air pollution and improve economic activities coupled with low carbon levels. The Indian government should exercise caution when adopting growth-promoting policies, as they may have negative environmental consequences. The government should establish a policy framework that ensures long-term demand for greenhouse gas emission reduction and actively promotes the use of technologies that contribute to a lower carbon economy. This will both maintain the country on a sustainable path and will also ensure the environment's conservation.

Measures to promote energy efficiency will ultimately reduce emissions. Indian authorities must adopt finance mechanisms to encourage investment in sustainable energy initiatives. India should implement tougher regulations to improve energy efficiency and energy-use programmes in order to reduce energy waste and replace conventional energy sources with cleaner and more economically viable alternatives. These would improve energy security while also lowering carbon emissions without negatively impacting economic growth.

Furthermore, the government must stimulate environmental awareness in the general public and focus on reducing levels of pollutant emissions from motor transport and from traditional practices such as burning stubble near New Delhi. Research and development must reflect the reality of global heating and the need for a sustainable economy. Such policies should consider the CO_2 emissions of the targeted sub-period of sample time, time scale and the persistent effects.

The direction of the future studies may be to analyse these dynamic relationships between energy consumption, economic growth and CO_2 emissions in India at disaggregated data in the key sectors such as industries and services.

Notes

1. Fourier analysis is mainly used for stationary time-series data; it applies the spectral tool to investigate the linkages between economic series. But, this method reflects only the frequencies and ignores the time information based on the time-series data. There are other Fourier techniques like the Windowed Fourier Transform analysis (WFT), which address the above-mentioned deficiencies, but as mentioned by Kaiser (2011), a potential drawback with the application of the WFT in time series analysis is that it suffers from the lack of accuracy and efficiency of simultaneous time–frequency localisation.
2. Wavelet coherence is used as a tool to identify whether the co-movement between each pair of economic variables is contagion or interdependence. Strong wavelet coherence at high frequencies indicates contagion. In contrast, strong wavelet coherence at low frequencies is identified as interdependence (Bodart & Candelon, 2009; Yang, Cai, Zhang, & Hamori, 2016).

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