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Long-Term US Economic Growth and the Carbon Dioxide Emissions Nexus: A Wavelet-Based Approach

Erdost Torun [1], Afife Duygu Ayhan Akdeniz [1], Erhan Demireli [2] and Simon Grima [3,*]

[1] Department of International Trade and Business, Faculty of Business, Dokuz Eylül University, 35220 Izmir, Turkey
[2] Department of Business Administration, Faculty of Economics and Administrative Science, Dokuz Eylül University, 35220 Izmir, Turkey
[3] Department of Insurance and Risk Management, Faculty of Economics, Management and Accountancy, University of Malta, 2080 Msida, Malta
* Correspondence: simon.grima@um.edu.mt

Abstract: Economic growth has significantly boomed carbon emissions in the global economy. However, there is an ongoing debate about the economic growth–carbon emission nexus for various economies in the literature. This paper investigates the short/long-term causal information flow between fossil-fuel-related carbon dioxide emissions (CO_2) and economic growth (GDP) in the US economy spanning from 1800 to 2014. Using wavelet-based-nonparametric Granger causality analysis, the empirical results indicate that (i) the long-run causal information flow running from GDP to CO_2 is positive, strong, uninterrupted and concentrated since the 1990s; (ii) the reverse causality is positive but interrupted, short-term and intensifying during the early 1990s. Due to strong and very long-term unidirectional causality findings, economic growth leads to environmental deterioration. Hence, for policymakers, environment-based growth policies and structural reforms can foreshadow energy-efficient policies by limiting carbon emissions. Hence, sustainable economic growth policies are expected to decelerate environmental problems and promote environmental sustainability. The findings can be attractive for other booming economies.

Keywords: CO_2 emissions; economic growth; continuous wavelet transform; causality

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1. Introduction

Globally, environmental deterioration has reached high levels and raised great concerns about global warming over the past few decades. Fossil-fuel-related carbon dioxide emissions (CO_2) are higher than at any time in history and still the largest source of anthropogenic greenhouse gas (GHG) emissions. Global fossil CO_2 emissions reached 37.9 gigatonnes of CO_2 (Gt CO_2) in 2018, following an upward trend since the first Industrial Revolution. The United States, on the other hand, has always been one of the top emitters that contributed the most to this increase. It experienced a continuous emissions growth since the end of the 19th century mainly through increases in population and industrialization. According to the US Environmental Protection Agency report, the largest source of US emissions is still burning fossil fuels for energy-related activities, and fossil-fuel-related CO_2 emissions accounted for 75.4 percent of total GHG emissions in 2018 [1] (EPA, 2020). Although its emissions from fossil fuels decreased approximately 12.3 percent since the peak at 5.7 Gt CO_2 in 2005, it is still the second-largest emitter after China, with an emission level of 5.0 Gt CO_2 in 2018. Over the last few decades, there has been growing literature on the relationship between economic growth and worsening environmental conditions. Many studies in the literature fail to establish a consensus on the existence of causality and its direction. Hence, the main objective of this paper is to examine the existence of a possible dynamic causal information flow patterns between fossil-fuel-related carbon dioxide emissions (CO_2) and economic growth (GDP) for the United States over the period 1800 to 2014 and produce new evidence on the very long-term growth-environment literature.

The Granger causality test is widely used to investigate economic growth–carbon emission nexus in the literature. With respect to the causality test, however, the conventional Granger causality test does not incorporate both time dependent causality changes and multiple time horizons at the same time. Hence, the main purpose of this paper is to apply nonparametric continuous wavelet Granger causality (CWTC, hereafter) test, developed by [2], to revisit the causal relationship between economic growth and carbon emission. There are two major advantages of the nonparametric CWTC test. First, continuous wavelet analysis provides time and frequency representation of the data, thus allowing for more information about the evolution of data. Therefore, the novel nonparametric CWTC test, an extension of the Granger causality test based on wavelet analysis, can easily deal with the issue of multiple time scales. Second, the nonparametric CWTC test is exempt from explicit autoregressive modeling that imposes difficulties on data parameterization, meaning that it is free from both model misspecification and distribution assumption under the modeling procedure.

Some advanced causality tests have actually been established over the first decade of the new millennium. Ref. [3] proposes a graphical approach test based on the spectral density matrix in the frequency domain, but restricts his research to the case of a weakly stationary process. Ref. [4] introduce a nonparametric causality test assuming that the time series is strictly stationary, which is not a realistic assumption. Moreover, this test relies on the residuals obtained from the vector autoregressive (VAR) model, which may not reflect the true dynamics of the data and suffers a misspecification of the bivariate model. In the newly expanding literature attempting to combine wavelet analysis and Granger causality, wavelet analysis is used as a part of causality analysis, especially as a preliminary step for decomposing the data before using the traditional causality test (e.g., [5–7]). Additionally, the concepts of coherence and phase difference have been employed to analyze the lead-lag relationship in the literature recently ([8–12]). Coherence can be defined as the counterpart of the coefficient of determination in the frequency dimension. Hence, correlation and coherence are slightly different in spectral analysis. Coherence measures the strength—not direction—of the co-movement tendency in the frequency domain. Ref. [13] address the resemblance between wavelet coherence and correlation coefficient since coherence can be assumed as a localized correlation coefficient in time–frequency space (For a detailed explanation of coherence and correlation, please refer to [2,14–17]. The correlation coefficient proposed by [15] and the CWTC test of [2] provide information on both the direction and strength of the correlation and causality patterns.

The CWTC test is superior to these kinds of methods in terms of being fully non-parametric and easy to interpret through providing direct positive/negative causality estimation output unlike other phase difference measures. Hence, CWTC is more efficient method to provide a three-dimensional causality map containing time-scale–strength evolution or causal information flow directly. In addition, refs. [2,18–20] prove that the nonparametric continuous wavelet Granger causality testing approach can represent the true time frequency pattern of a series and correctly cover the true network interaction pattern, implying that this test is suitable for time series analysis and revealing information flow among a series.

This paper contributes to the related literature in a two-fold manner: (i) To the authors' best knowledge, this paper is the first in the literature to empirically apply the CWTC test to analyze the causality relationship between CO_2 emissions and US GDP growth for such a long period. This paper comprehensively investigates the causal information flow between US economic growth and carbon emission in detail. This paper shows new evidence that causal information flow may change depending on both the time scales and time. (ii) The paper examines the economic growth–carbon emission nexus for two-century-long data to provide new insights about the evolution of the nexus. Hence, this paper provides new knowledge on this two-century-long time and scale-based evolution of the information flow between economic growth and carbon dioxide emissions in US. Specifically, this paper presents two main conclusions. First, there may not be just one dichotomous answer about the Granger causality test for the economic growth–carbon emission nexus in a time domain, as data exhibit different causal information flows for different time scales and have complex and detailed causal information flow patterns that the traditional Granger causality test, which provides dichotomous results, cannot fully explain in detail. Second, there may not be only one theory explaining the economic growth–carbon relationship nexus for all scales, but rather each theory may be valid for a specific time scale.

The studies in the related literature mainly employ conventional time series and panel data methodologies to test a possible causality connection between environmental deterioration and economic growth. These methodologies can investigate the relationship in terms of time or cross-sectional dimensions of the related variables, but cannot capture the relationship patterns in their frequency dimension. Hence, this study considers both time and frequency dimensional features of variables through wavelet-based causality testing methodology. This methodology is useful for analyzing causal relationships evolving with time at different frequencies. It is an efficient tool for investigating how the different periodic patterns of the data components evolve over time. One of the advantages of frequency representation is that one can decompose the causal connections based on periodic dynamics and isolate the long-term (low frequency) causal patterns from the short-term (high frequency) causal patterns and see whether the short- or long-term causalities change over time.

Our analysis provides more insights to the policymakers and economists to evaluate changes in the causality information flow between economic growth carbon emissions and in terms of both time and long/short-term (scale or frequency) evolution. Through carbon emission, economic growth policies may evoke environmental problems. Therefore, conducting environmentally friendly and sustainable economic growth policies can limit carbon emissions. In addition to monetary and fiscal policies, structural reforms can mitigate the economic growth–CO_2 nexus in the US economy from a long-term perspective.

The rest of the paper is organized as follows: Section 2 explains a brief discussion of the literature. Section 3 discusses empirical methodology. Section 4 provides data sources for the study and presents empirical findings of the research. The last section concludes the study and discusses the policy implications of the results.

2. Literature Review

In the last three decades, one of the subjects that has received the greatest attention in the economics literature is the relationship between environmental contaminants, economic growth, and energy use. The associated literature includes three research subfields. The first strand focuses on the relationship between environmental pollutants and economic expansion in order to evaluate the Environmental Kuznets Curve (EKC) theory. An expanding corpus of literature has investigated this link between economic growth and environmental pollution in the wake of the seminal paper of [21]. The empirical data are still debatable though. The relationship between economic production and energy use is the subject of the second study stream. Following the original paper of [22], other studies have looked at the causal connection between GDP and energy usage. The literature focusing on the causal relationship between energy consumption and economic growth is thoroughly reviewed by [23,24]. These two study threads are combined in the third stream of inquiry, which mainly focuses on the dynamic relationships between energy use, environmental contaminants, and economic growth. The findings of empirical papers focusing on the relationship between the energy–environment–growth nexus in the US and other nations are presented in Table 1. Table 1 leads us to the conclusion that there is still no clear causal link between the income nexus for energy use and CO_2 emissions. Depending on the sample period, methodology, and sample country utilized in the analysis, different conclusions exist about causality orientations. Additionally, to detect any potential causal relationships, these research employ time series or panel data techniques.

Table 1. Papers on the energy–environment–growth relationship.

Study	Country	Period	Methodology	Causality
[22]	US	1947–1974	GC	N→E
[25]	US	January 1973–March 1978	GC	E→P
[26]	US	1950–1970	Sim's GC	N—E
[27]	US	1947–1979	Sims' GC	N—E
[28]	US	1947–1987	GC	N→E
[29]	US	1974–1990	GC	G—E
[30]	US	1947–1990	Multivariate VAR model	E→G
[31]	US	1947–1990	GC	G—E
[32]	US	1948–1994	GC	E→G
[33]	Norway	1973–2003	GC	G→C
[34]	France	1960–2000	ECM-based GC	G→C G→E
[35]	US	1960–2004	Toda and Yamamoto (1995)	E—G G—C E→C
[36]	Malaysia	1971–1999	ECM-based GC	C→G E↔G
[37]	US	1949–2006	Toda–Yamamoto (1995)	G—E
[38]	Turkey	1960–2005	VECM-based GC	C↔G C↔G^2 C→E
[39]	China	1960–2007	Toda and Yamamoto (1995)	C—G G→E E→C
[40]	China	1975–2005	Pair-wise GC	G→C E→C
[41]	Turkey	1960–2000	Toda and Yamamoto (1995)	C—G C→E
[42]	US	1960–2007	Toda and Yamamoto (1995)	G↔C G→RE
[43]	India	1971–2006	VECM-based GC	C—G
[44]	France	1960–2003	GC	G→C
[45]	Brazil	1980–2007	ECM-based GC	G→C
[46]	China	1995–2007	VECM-based GC	G→C
[47]	Malaysia	1980–2009	VECM-based GC	C→G
[48]	Philippines	1965−2010	ECM-based GC	E↔G E↔C C→G
[49]	US	1973Q1–2014Q1	Time-varying GC	E↔G 1990s G→E 2000s
[50]	22 Central and South American Countries	1995–2010	GC	G→E (short-run) G→C (long-run)
[51]	China	1995–2015	FE, PSCE, N-W, FGLS regression models	G→C
[52]	Belt and Road Initiative Countries	1995–2015	Panel causality and cointegration models	EI, G↔C
[53]	65 countries	1965–2019	Panel causality and cointegration models	G↔ C
[54]	Belt and Road Initiative Countries	1991–2016	Tapio decoupling model, Kaya–LMDI model	G→C
[55]	BRICS countries	1990–2014	ARDL model, causality test	G→C
[56]	UK	1985–2017	ARDL model, causality test	G→C
[57]	Kuwait	1971–2017	ARDL, causality test	G→C
[58]	China	1971–2016	quantile-on-quantile regression, Granger causality	G→C
[59]	Mexico	1990–2018	ARDL, FMOLS models, and causality	G→C
[60]	Brazil	1965–2019	ARDL, DOLS, FMOLS, Maki cointegration, Wavelet coherence	E, C→G
[61]	Indonesia	1965–2019	ARDL, DOLS models	G↔C
[62]	ECO member countries	1990–2014	FMOLS model and causality test	G↔C
[63]	Portugal	1980–2018	FDC causality, Wavelet coherence	G→C
[64]	Sweden	1965–2019	quantile-on-quantile regression	G→C

Notes: → refers to the unidirectional causality or relationship impact direction; ↔ and — denote bivariate causality or relationship impact direction, and no causality or no relationship impact direction, respectively. G, N, E, P, and C refer to gross domestic product, gross national product, energy consumption, employment, and CO_2 emissions, respectively. GC denotes Granger causality testing framework. VECM denotes the vector error correction model, and ECM is the error correction model. EI denotes energy intensity data.

Recent studies have used the wavelet methodology to evaluate the causation hypotheses by taking the time and frequency dimensions of the pertinent data into account. The discrete wavelet transform (DWT) is typically used to observe the correlations between related variables. In the Turkish manufacturing sector from 1968 to 2002, Ref. [65] looked at multi-scale causality between economic growth and electricity usage. The results of the study indicated a short-term bidirectional relationship between energy consumption and GNP, but long-term causality between GNP and energy consumption was also demonstrated. By using DWT for the quarterly data from 1973Q1 to 2012Q1, Ref. [66] examined the causal relationship between economic growth and energy consumption in the US. According to their findings, economic growth affects energy consumption in the medium and long run, while energy consumption affects economic growth in the near term. For six oil-exporting nations between 1980 and 2012, Ref. [67] examinated the connection between carbon emissions, energy usage, and economic growth. According to their findings, there is a bivariate relationship between economic growth and CO_2 emissions as well as between economic growth and energy consumption, and there are no feedback effects in the causal chain connecting carbon emissions and energy consumption. For 74 nations between the years of 1972 and 2014, Ref. [68] examined the causality relationship between GDP and energy usage. Their findings implied that, over the long term, there is a bivariate causality relationship between electrical energy usage and GDP. However, in the short and medium term, GDP influences electricity consumption, whereas the opposite is not true. For data from January 1973 to December 2018, Ref. [69] examined the short- to medium-run relationships between economic activity and carbon emissions in the US. Their findings indicated that there is no discernible relationship between emissions and short-term economic activity. However, in medium-term cycles of roughly one to three years, there is a considerable relationship between economic activity and carbon emissions.

The economic growth–environment nexus is being investigated in an increasing number of papers employing the continuous wavelet transform (CWT). For instance, Ref. [70] examined the connection between renewable energy consumption and industrial productivity in the United States using monthly data with the period from 1981 to 2013. The study's findings showed that using renewable energy increases industrial production at both lower and higher frequencies in a favorable and significant way. Ref. [71] used quarterly data with the period from the 2005Q1 to 2015Q3 to study the co-movements between real production and aggregate and sectoral energy consumption levels in the United States. Their findings demonstrated that both renewable and non-renewable energy consumption is outpacing real production and that the consumption of all renewable and non-renewable sources moves in tandem with real output. Using both discrete and continuous wavelet transform for the period January 1973 to July 2015 [72] studied the relationships between economic growth, energy consumption, and carbon emissions for the transportation sector in the United States. Their findings indicated that, in the short run, there exists unidirectional causal relationship between energy use and carbon emissions and economic growth, but that, in the long and very long runs, economic growth leads energy usage and emissions. The impact of renewable energy sources on industrial production in the US from January 1989 to November 2016 was examined by [73]. According to their findings, both short- and long-term cycles of industrial output are positively impacted by renewable energy sources.

According to a review of the body of research on wavelet causation, the majority of studies have either employed shorter time intervals or have concentrated on the causality connection between energy usage and economic output. Additionally, Ref. [74] served as the foundation for the CWT methodology employed in earlier investigations (1998). This study set itself apart from earlier research by employing a more recent methodology, the CWT-based Granger causality method proposed by [2], to investigate the causality relationship between carbon emissions from fossil fuels and economic growth in the United States over a very long time period, 1800–2014. This technique avoids the requirement for minimum-phase transfer functions and can pinpoint causality both in terms of time and frequency domains ([75]).

Ref. [50] found evidence in favor of short-run unidirectional causality connection between renewable energy and economic growth for 22 nations. Moreover, economic growth leads higher carbon emission in the long run. Thus, they conclude that economic expansion eventually results in larger carbon emissions. Ref. [51] examined how economic expansion influences carbon emissions in China by looking at the country at the national and regional levels from 1995 to 2015. Ref. [60] demonstrated how energy use and carbon emissions can be used to forecast economic expansion in Brazil from 1965 to 2019.

Ref. [76] examined causal information flow between GDP and carbon dioxide emissions in 79 countries including US for the period of 1980–2014. The results indicated that, in countries with high average per capita income, GDP and carbon dioxide emission have a bidirectional causality in both the short and long run. Investigating the nexus between economic growth and carbon dioxide emissions in G20 countries for the period 1992 to 2014, Ref. [77] found a bidirectional causality relationship between economic growth and pollution.

Refs. [78,79] examined the relationship between carbon dioxide emissions and economic growth in US, and found evidence in favor of the environmental Kuznets curve hypothesis across states. Hence, the findings indicated that the level of CO_2 emissions rises until peak of economic growth, then the level of CO_2 emissions decreases, yielding inverted U-shaped relationship between CO_2 emissions and economic growth in US. They emphasized that higher levels of economic development will eventually reduce pollution. Similarly, Ref. [80] suggested US government use of renewable energy sources due to fact that they play a dominant role in reducing carbon dioxide emissions, while non-renewable energy contributes to environmental degradation. Moreover, economic expansion and globalization helps to minimize environmental pollution after a threshold, based on the analysis results in the US for the period 1980–2016.

Ref. [81], pointing out the long-term relationship between carbon emissions and GDP, stresses that GDP have a beneficial impact on carbon emissions. The results indicate that the amount of carbon emitted decreases when the economy expands for the US economy from 1985 to 2020. Ref. [82], investigating the leading factors for the carbon dioxide emission for the six largest world emitter countries for the period of 1990–2018, addressed that results are mixed for the countries. However, energy intensity leads both GDP and carbon dioxide emissions. Additionally, there exist univariate causality from carbon emission to GDP for Russia and also univariate causality from GDP to carbon emission for Japan. Through analyzing the causal relationship between economic policy uncertainty and carbon emissions, Ref. [83] found that policy uncertainty affects the carbon emission growth for US sectors when carbon emission growth is at a lower level than at a higher level. Interestingly, Ref. [84] mentioned that that clean energy consumption does not contribute to emissions reduction in the long run for France. The results revealed the causality from political uncertainty to economic growth and emissions, giving importance to the impact of policy implication on carbon emissions. Additionally, they reported that both economic growth and economic policy uncertainty increases carbon dioxide emission and bidirectional causal information flow between carbon dioxide emission and economic growth and political uncertainty and carbon dioxide emission for the period 1987–2019.

On the other hand, Ref. [85] pointed out that the negative change in economic policy uncertainty facilitates emissions in the USA in the long and short run, whereas its positive change does not produce any significant effect. They emphasized that policies should aim to adjust fossil energy consumption through developing green and clean energy sources for energy resource diversification and low-carbon intensification. Ref. [86] examined the relationship between carbon dioxide emissions and economic development in ten different countries, including US, from 2010 to 2019. The results reveal long-run positive association between GDP and carbon emission where association pattern is negative in the short run.

3. Methodology

The underlying idea behind wavelet analysis is to simultaneously disintegrate data into components varying in both time and frequency dimensions. Unlike the conventional time series and Fourier transformation techniques, wavelet analysis enables spectral analysis to examine distinct periodic components of data as they change over time and frequency [87]. Fourier analysis reveals frequency structures in a given dataset; however, Fourier analysis fails to reveal any temporal information in time dimension. Wavelet analysis outperforms Fourier analysis by taking into account the dynamic nature of the component in the time and frequency scale. Thus, wavelet analysis is considered as nonstationary data analysis tool unlike Fourier analysis. Wavelet analysis has become popular in economic and financial data analysis as most of the economics and financial data have nonstationary nature. Therefore, wavelets have become widely used in economics and finance to examine temporal fluctuations between variables on different horizons.

In wavelet analysis, decomposition step is executed through either discrete (DWT) or continuous (CWT) wavelet transforms. Initial applications of wavelets have generally focused on the DWT [88–93]. More recently, there has been a growing literature employing the CWT (including, [10,16,88–101]). The CWT, unlike the DWT, have advantages of more wavelet function alternative to use and providing easily interpretable analysis output, and CWT efficiently investigate common dynamics and phase discrepancies [75,87,102]. In this study, we uses the CWT for a recent causality test of [2], which modifies the correlation measure in CWT proposed by [15] by including a specific indicator function for a specific type of causality investigated.

3.1. Continuous Wavelet Transform

A wavelet can be defined as a rapidly ascending and descending wave-shaped function with zero mean. Convolution of data with repeatedly shifting and stretching wavelet function of $\Psi_{s,\tau}(t) = \Psi\left((t-\tau)/s\right)/\sqrt{s}$ provides the CWT coefficients:

$$W_X(s,\ \tau) = (x * \Psi_{s,\ \tau})(t) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\widetilde{\Psi}\left(\frac{t-\tau}{s}\right)dt \quad (1)$$

where $\widetilde{\Psi}(\cdot)$ denotes the complex conjugate of $\Psi(\cdot)$. s and τ are the wavelet scale and localized time index parameters, respectively. Stretching via various s parameter values and shifting wavelet function along τ parameter values provides three-dimensional data representation of data. Following [2], the Morlet wavelet function, invented by [103], was used in this study. The Morlet wavelet function is a function that a plane wave modulated by a Gaussian: $\Psi(\eta) = \pi^{-1/4}exp(i\omega\eta)exp(-\eta/2)$ with $\omega = \omega_0 = 6$. ω is the nondimensional frequency, and η is nondimensional time (see [74]). The Gaussian envelop, $exp(-\eta/2)$, effectively optimizes the location of the wavelet between the resolutions in time and frequency, which are determined by the dimensionless frequency. In the literature, the concepts of scale and frequency are almost the same $(s \approx f)$. The wavelet is stretched trough parameter s so that $\eta = s{\cdot}t$. Morlet wavelet optimizes the time–frequency distribution of the data. Moreover, the Morlet wavelet is suitable for oscillation analysis with time varying scale and amplitude. Moreover, it captures information about the data's frequency pattern. Hence, it is applicable for non-stationary data containing transient or irregular cycles with varying periods ([104]). The discretization of Equation (1) for data $\{x_n : n = 1, 2, \ldots, N\}$ provides the wavelet spectrum:

$$W_X^m(s,\tau) = \frac{\delta t}{\sqrt{s}}\sum x_n \widetilde{\Psi}\left((m-n)\frac{\delta t}{s}\right),\ \mathrm{m} = 1,\ 2,\ \ldots,\ \mathrm{N}-1. \quad (2)$$

where δt refers to uniform increment size. The wavelet power spectrum $\left|W_X^m(s,\ \tau)\right|^2$ contains the information on the variability in time–frequency dimensions. The cross-spectrum of data x_n and y_n, which captures covariance patterns in frequency domain, is defined as $W_{XY}^m(s,\tau) = W_X^m(s,\tau)\widetilde{W}_Y^m(s,\tau)$, where $\widetilde{W}_Y^m\ (s,\ \tau)$ denotes the complex conjugate matrix of $W_Y^m\ (s,\ \tau)$. Then, for variable x , wavelet transform is decomposed into the real and imaginary parts through $W_X^m(s,\ \tau) = \Re\left\{W_X^m\ (s,\ \tau)\right\} + i\Im\{W_X^m(s,\ \tau)\}$ to compute the local phase, $\varphi_X(s,\ \tau) = \tan^{-1}\left\{\frac{\Im\left(W_X^m(s,\ \tau)\right)}{\Re\left(W_X^m\ (s,\ \tau)\right)}\right\}$. Moreover, the phase difference, which contains information on lead-lag relationship patterns, is used to calculate spectral Granger causality through wavelet correlation (the same decomposition also applies to the variable y). Ref. [15] defines wavelet correlation as:

$$\rho_{XY}(s,\ \tau) = \frac{\zeta\{s^{-1}|\Re(W^{m}_{XY}(s,\ \tau))|\}}{\zeta\left\{s^{-1}\sqrt{|W^{m}_{X}(s,\ \tau)|^{2}}\right\}\cdot\zeta\left\{s^{-1}\sqrt{|W^{m}_{Y}(s,\ \tau)|^{2}}\right\}} \tag{3}$$

where $\zeta(\cdot) = \zeta_{scale}(\zeta_{time}(\cdot))$. ζ_{scale} and ζ_{time} refer to the operators to smooth spectrum values for the scale axis and time axis, respectively.

3.2. Continuous Wavelet Transform-Based Causality

Ref. [2] proposed the novel CWT based causality measure, with the modification of the correlation formula in Equation (3) by including a specific indicator function, which in turn is based on the phase difference calculation. The phase difference between x and y data pair is defined as:

$$\phi_{XY}(s,\ \tau) = \phi_{X}(s,\ \tau) - \phi_{Y}(s,\ \tau) = \tan^{-1}\left(\frac{\Im(W^{m}_{XY}(s,\ \tau))}{\Re\ (W^{m}_{XY}\ (s,\ \tau))}\right) \tag{4}$$

with the range $-\pi \le \phi_{XY}(s,\ \tau) \le \pi$ that can be subdivided into four intervals (see [87,96]). Each interval provides information on lead-lag pattern and the direction of the causal information flow. Intervals of $\phi_{XY}(s,\ \tau) \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{XY}(s,\ \tau) \in \left(-\frac{\pi}{2},\ 0\right)$ indicate that two variables comoves in positive direction (or they move in-phase). Alternatively, phase difference within the intervals of $\phi_{XY}(s,\ \tau) \in \left(\frac{\pi}{2},\ \pi\right)$ or $\phi_{XY}(s,\ \tau) \in \left(-\pi, -\frac{\pi}{2}\right)$ indicate that two variables co-move negatively (or they move out-of-phase). Further, $\phi_{XY}(s,\ \tau) \in \left(-\frac{\pi}{2},\ 0\right)$ or $\phi_{XY}(s,\ \tau) \in \left(\frac{\pi}{2},\ \pi\right)$ indicates that y leads x, in other words, phase difference in these intervals reveals that x has causal information flow on y. $\phi_{XY}(s,\ \tau) \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{XY}(s,\ \tau) \in \left(-\pi, -\frac{\pi}{2}\right)$ denote x leads y.

The indicator function is a mathematical function using phase difference interval information to separate integrated causal links from the non-causal patterns. Moreover, indicator functions measure the direction of the causal information flow. Indicator functions are set to one for the given defined phase difference subinterval and zero otherwise. Thus, indicator functions are considered as restriction imposed on wavelet correlations for both specific directions and the lead-lag causal information flow. For instance, an indicator function investigating only whether x leads to y, ignoring the direction of the causality, is defined as (other directional indicator functions to investigate in-phase or out-of-phase predictive information flows from x to y or from y to x are provided in [2]):

$$I_{Y\longrightarrow X}(s,\ \tau) = \begin{cases} 1,\ if\ \phi_{XY}(s,\ \tau) \in \left(0,\ \frac{\pi}{2}\right) \cup\ \left(-\pi, -\frac{\pi}{2}\right) \\ 0,\ otherwise \end{cases}. \tag{5}$$

Augmenting [15]'s CWT-based correlation formula with the indicator function $I_{Y\longrightarrow X}(s,\ \tau)$ yields the following CWT-based Granger causality test:

$$G_{Y\longrightarrow X}(s,\ \tau) = \frac{\zeta\{s^{-1}|\Re(W^{m}_{XY}(s,\ \tau))I_{Y\to X}(s,\ \tau)|\}}{\zeta\left\{s^{-1}\sqrt{|W^{m}_{X}(s,\ \tau)|^{2}}\right\}\zeta\left\{s^{-1}\sqrt{|W^{m}_{Y}(s,\ \tau)|^{2}}\right\}} \tag{6}$$

where $G_{Y\longrightarrow X}(s,\ \tau)$ is positive causal movement measure (in-phase causality) in the case of the $I_{Y\longrightarrow X}(s,\ \tau)$ indicator function being true for the intervals of $\phi_{XY}(s,\ \tau) \in \left(0,\ \frac{\pi}{2}\right)$ or $\phi_{XY}(s,\ \tau) \in \left(-\frac{\pi}{2}, 0\right)$. This Granger causality measure in CWT can separately investigate positive and negative causality through indicator functions specifically defined for the required phase-difference range. Similarly, predictive information flows from x to y are investigated through $G_{X\longrightarrow Y}(s,\ \tau)$ through indicator function $I_{X\longrightarrow Y}(s,\ \tau)$.

Equation (6) is an alternative to the wavelet causality measure in CWT proposed by [19], which suffers from spectral matrix factorization calculation failure. This nonparametric technique, which demands high autoregressive order because to the high correlation structure in the parametric approach, is particularly crucial for time series with oscillations and extended memory. As a result, the nonparametric Granger causality technique eliminates the chance of erroneous causation brought on by incorrectly described errors. This CWT causality measure is computationally efficient because it exempts from both Fourier transformation and any assumption about specification of the autoregressive model lag order (for detailed information about features of the continuous wavelet transform causality method and simulation results, please see [2]). This methodology deviates from the conventional parametric Granger causality method that (i) lacks the ability to fit the complex structure of time series data, (ii) requires autoregressive modeling which imposes difficulties on data parameterization, and (iii) assumes that a single dichotomous causality result that is assumed to be held for the whole period investigated.

3.3. Data

This paper employed annual data on real GDP per capita and carbon emissions for the United States from 1800 to 2014. Real GDP per capita (at 2012 constant prices in US Dollars) data were based on the study of [105] (the data are available at https://www.measuringworth.com/datasets/usgdp, accessed on 10 April 2016). The series on total fossil-fuel emissions were obtained from Carbon Dioxide Information Analysis Center (CDIAC) and based on the study of [106] (See [106] for details. The data are available at https://cdiac.ess-dive.lbl.gov/ftp/ndp030/nation.1751_2014.ems, accessed on 14 April 2018). Both series were used in natural logarithms, and logarithmic differences were used for the analysis.

4. Results

Figure 1 exhibits the results of CWT-based causality connections between variables. Panels (a) and (b) show the time–frequency CWT plots of causal effects from GDP to CO_2 and from CO_2 to GDP in level curves as there are three dimensions of time, frequency, and causality strength involved. The color code represents the height of the level curves, which runs from 0 to 1, and indicates the strength of the causality between variables. The vertical axis reports the period (scale or reverse of frequency) reported in years, while the horizontal axis reports the time. Panel (a) shows CWTC causality from GDP to CO_2. Panel (a) exhibits short-dated causality from GDP to CO_2 for the periods of (1860–1880), 1910s, in the end of 1920s, (end of 1950s–beginning of 1960s), and in the 1970s at the highest scale band of (1–4) years. The relatively transient nature of these causal information flows indicates the relatively weak dynamics behind them. Additionally, weak and short-dated causality occurs at around 6 years' scale in the period of (1820–1830). CWTC detects more persistent, thus strong, causality pattern in the period of (end of 1850s–2014) with a transient break around 1900s at (8–16) years' scale band. These patterns are considered as strong due to its persistent nature. In terms of statistical significance, this causal information flow becomes stronger in the period of (1870–1900) and (1910s–2014). Additionally, causal flow is seen in the period of (1900–2014) and becomes stronger in the period of (1910–2014) at (16–32) years' scale band. Combining the causality patterns seen in (8–16) and (16–32) years' scale band together, the most persistent pattern is seen in the period of (1850s–2014) at (8–32) years' scale band. The causality pattern with the lowest scale band occurs in the period of (1900s-end of 1950s) at around 40 years' scale band, but it is relatively weak. In summary, Panel (a) shows a strong causality from GDP to CO_2 with the 8~16-year frequency, and this causality relationship has continued from the 1860s to the present. However, a much stronger causal effects are observed between 1870 and 1890 on the 8~16-year frequency and between 1920 and 1960 on the 16~32-year frequency. There was also causality between 1900 and 1960 on the 32-year frequency. Relatively high-frequency causality is also observed on the 4-year frequency, but it is not regular.

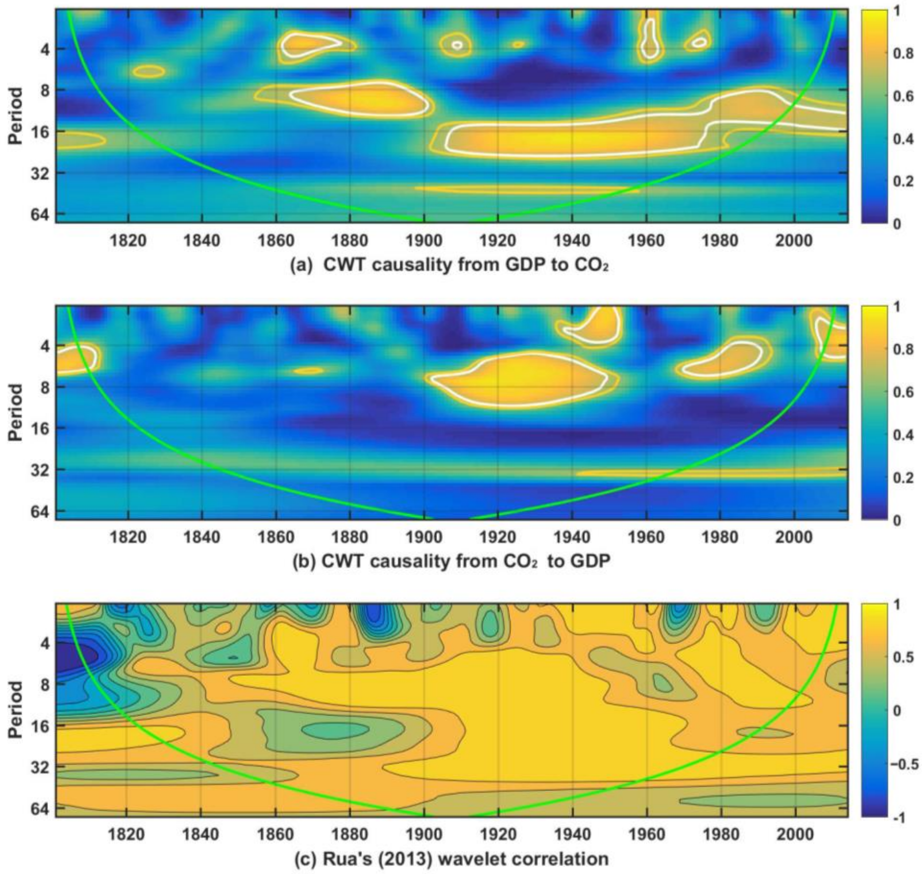

Figure 1. Continuous wavelet transform-based causality patterns between economic growth and carbon emissions. The color code indicates the strength of causality. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of ARMA (1,1) process with null hypothesis of no statistical significance. The green line represents the cone-of-influence (COI) defining the areas affected by the edge effects [13].

Panel (b) shows CWTC causality from CO_2 to GDP. Panel (b) exhibits short-dated causality from CO_2 to GDP for the periods of 1810s, (end of 1830s–1950s), 1980s, and 2010s at the highest scale band of (1–4) years. The relatively transient nature of these causal information flows indicates the relatively weak dynamics behind them. CWTC also detects transient causality patterns in the period of 1810s, in the beginning of 1870s, (1900–1950s), (1970s–1990s), and 2010s at (4–8) years' scale band. Additionally, causal flow is seen in the period of (1900–1950s) at (8–10) years' scale band. The causality pattern with the highest scale band occurs in the period of (1940s–2014) at around 32 years' scale band, but it is relatively weak. In summary, in Panel (b), we observe a strong but intermittent causality running from CO_2 to GDP between 1900–1990 on an 8-year frequency. Causality from CO_2 to GDP with a 32-year frequency is also seen after 1940. Intermittent and relatively high-frequency causality is observed on the 4-year frequency and between 1970–1990, and long-run causality is seen between 1970–1990. Panel (c) exhibits the continuous wavelet transform-based correlation measure proposed by [15]. These two variables generally move together since the correlation is high in all periods. It also shows that the periods of causality connection observed in Panels (a) and (b) correspond to the period of high positive correlation between the carbon emission and economic growth.

In summary, there is a strong causality information flow running from GDP to CO_2 after the 1860s for different year frequencies, indicating that economic growth leads to environmental degradation as expected. This relationship became significant and uninterrupted during the last decades. However, the contrast causality is interrupted and valid for the short-term frequencies.

Figure 2 shows the positive (in phase) causality relationship patterns in Panels (a) and (b) and the negative (out of phase) causality relationship patterns in Panels (c) and (d). In Figure 2, we observe that the causality relationship expressed in Figure 1 is positive, and there is no negative causality between the two variables. Panel (a) exhibits a positive Granger causal information flow from GDP to CO_2. Generally, we observe a strong positive causal effect from GDP to CO_2 after the 1860s for midterm frequencies as an adjustment of high economic growth comes up with environmental degradation. The uninterrupted causality concentrated during the last decades. On the other hand, the reverse positive causality is interrupted, acceptable for the short-term frequencies and intensifying early 1990s.

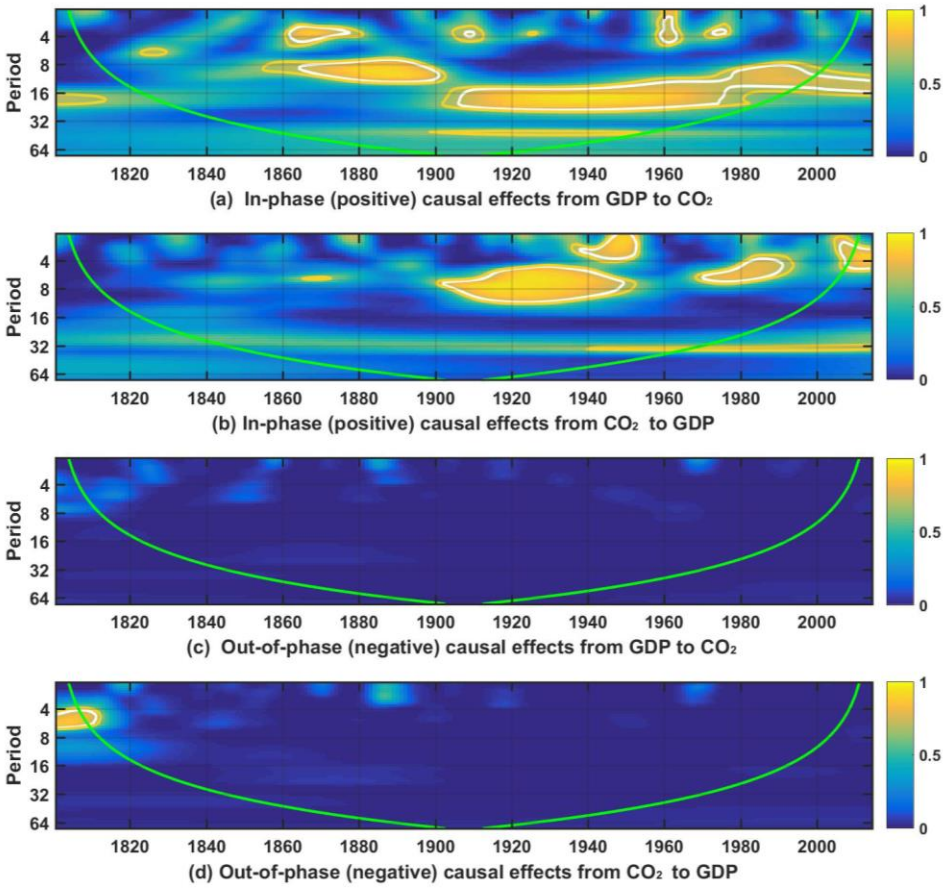

Figure 2. Positive (in phase) and negative (out of phase) continuous wavelet transform-based causality patterns between economic growth and carbon emissions. The color code indicates the strength of causality. The x-axis reports the years, and the y-axis reports the period (reverse of frequency) defined in terms of years. The white (yellow) contour indicates the 5% (10%) significance level constructed based on 3000 Monte Carlo simulations of ARMA (1,1) process with null hypothesis of no statistical significance. The green line represents the cone-of-influence (COI) defining the areas affected by the edge effects.

Starting from the 1850s to 1960, the world economies, particularly the US, faced a constant growth of emissions through expeditious industrialization and population growth, which led to a rapid economic growth. This increase was interrupted only because of some historical events, such as the Great Depression and the World War II in in the 1930s and 1940s. Our findings indicate that strong positive causality from GDP to CO_2 occurs in the period 1850 to 1900. Rapid industrialization and population growth may explain the existence of strong positive causality from GDP to CO_2 in 1850–1900. By 1900, oil and its byproducts had become widely used in the US industry, even in the country's daily life.

In the 1950s, the US became an oil importer due to the growth of oil consumption, which made the country dependent on the new oil supply.

5. Conclusions

Economic growth is one of the drivers of carbon emissions (CO_2), while the US economy is one of the top emitters in the world. Although it was interrupted due to some shocks, such as the Great Depression and World War II, the increase in CO_2 is attributed to many long-term and short-term factors, including rapid industrialization, population growth, changing energy prices, economic growth, and new technologies and regulations.

In the literature, there is an ongoing debate about the economic growth–carbon emission relationship for various economies (Table 1). This paper examined both the short- and long-run causality patterns between carbon emission and economic growth on the US economy, spanning the very long period from 1800 to 2014. In this study, the application of wavelet-based-nonparametric Granger causality analysis allowed us to investigate the causality dynamics between economic growth and carbon emissions in various time scales and hence, enables us to identify not only the causality dynamics between the two variables both in the long term and in the short term, but also the evolution of causality patterns.

By employing a novel approach to causality, a time–frequency–strength framework of causality measure developed by [2], we observed a bidirectional causality between GDP and CO_2 in the US economy. However, the long-run causality from GDP to CO_2 is strong, uninterrupted and positive, indicating that economic growth leads to environmental degradation. It concentrated during the last decades (since the 1990s). However, the reverse causality is interrupted, short-term and positive intensifying during the early 1990s.

Based on the results, a rise in economic growth increases carbon emissions. It is widely recognized that carbon emission is the main cause of environmental problems. Therefore, the environment-based economic growth strategies are a part of sustainable development. By promoting environmentally friendly and sustainable economic growth policies, carbon emissions can be reduced both in the short term and long term in the US economy. Since the monetary and fiscal policies have short-term effects on the domestic economy, structural reforms, such as renewable energy infrastructure, energy-efficient investments (or clean production technologies), tax subsidies for green growth, and environmental regulations, can ease the growth–CO_2 nexus in the US economy for long-term perspective.

The limitation of the current research is that the empirical analysis concentrated on the relationship economic growth and carbon dioxide emission. Due to lack of long data for new sectors driving US economic growth, such as information technology, or green/renewable energy sectors, this research focuses on bivariate causal information flow analysis. Future studies could be performed on a broader sample of nations with additional drivers of carbon dioxide emissions when longer data becomes available in the future. Likewise, the research might be improved by incorporating important factors into the causality analysis, such as economic complexity, renewable energy, globalization, financial development, and information technology when data become feasible in the future.

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