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Worldwide fluctuations in carbon emissions: Characterization and synchronization

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ABSTRACT

Coordinated and cooperative efforts among international actors are necessary for climate policy effectiveness. From a macroeconomic perspective, the greater the synchronization of business cycles, the greater the potential for policy coordination and joint decision making. In light of the procyclical behaviour between the business cycle and the carbon emission cycle, this work tries to shed light on carbon emission fluctuations of sixteen major developed and developing economies during 1946–2021. In analogy with "classical" business cycle research, the analysis dates expansionary and contractionary phases, determines their durations and amplitudes. It also inspects emission synchronization between pairs and groups of countries in order to assess their degree of carbon integration. Carbon emission fluctuations are mostly an expansionary phenomenon. Compared to developed countries, developing countries feature on average longer cycles (i.e., a lower number of full cycles), less time spent in contraction, longer expansionary phases, shorter contractionary phases and larger absolute amplitudes. Pairwise carbon emission fluctuations are synchronized in 34.2% cases. Developed economies have their own common emission cycle. As for developing economies, results are heterogeneous. Only part of them, in fact, shows evidence of a common carbon emission cycle despite a relatively recent history of cooperation, heterogeneous geographical locations and socio-cultural features.

1. Introduction

The economic act of producing goods necessarily implies the simultaneous discharge of "bads" into environmental sinks such as soil, water, and air. Among wastes, greenhouse gases (*GHG*) – primarily carbon dioxide (CO_2) – are believed to be the major responsibles to global warming, that is, the long-term increase in average global temperatures. International actors are expected to work in a coordinated (Nordhaus, 2019) and cooperative (Keohane and Victor, 2016) manner to make climate policy effective. Macroeconomic integration across different actors enhances business cycle synchronization (Frankel and Rose, 1998), laying the basis for greater policy coordination and shared decision making (Gouveia and Correia, 2013). Given the procyclical relationship between the business cycle and the carbon emission cycle (Doda, 2014), this work adopts a macroeconomic standpoint to study how carbon emissions fluctuate and test their synchronization across different countries to enhance carbon policy coordination. Differences are stressed between developed – G7 (Canada, France, Germany, Great Britain, Italy, Japan, and United States) countries – and developing economies – BRICS (Brazil, China, India, Russia, South Africa) and MIST (Indonesia, Mexico, South Korea, Turkey) countries. Knowledge about the recurrent movements of carbon emissions would enhance their predictability. Studying their degree of coupling might help assessing the mutual responses of one or more countries to domestic and international carbon policies. Paralleling fiscal and monetary policy (Chang, 2011), should fluctuations of carbon emissions be synchronized within a certain economic area, countries could potentially benefit from higher carbon policy coordination.

In light of the foregoing, this work thoroughly and systematically addresses carbon emission fluctuations. It makes a step back with respect to extant literature, exploring the cyclical features of carbon dioxide emissions through a "classical" (Burns and Mitchell, 1946; Artis et al., 1997) framework that avoids any filtering technique. In line with most business cycle literature, it focuses on the post-World War II period (1946–2021). Due to its "classical" setting, this work complements and extends the findings of Zerbo and Darné (2019) and Churchill et al. (2020) with a new pattern of turning points and a new detailed characterization of the cycle in terms of number of complete cycles, the fraction of time spent in contraction, average durations and average amplitudes. As an original contribution, this work provides a

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synchronization analysis of international carbon emission fluctuations, endowing academics as well as practitioners with a well-established macroeconomic tool to assess the mutual behaviour of carbon emissions between countries.

The work is organized as follows: Section 2 presents a basic literature review; Section 3 describes the core characteristics of the dataset and details the methodology employed; Section 4 reports and discusses the results of the analysis; Section 5 summarizes and contextualizes the main findings. The Appendix at the end contains the list of turning points characterizing carbon emission fluctuations for each country considered.

2. Literature review

Being driven by human activities, the cyclical features of carbon emissions distinguish themselves from and at the same alter the natural global carbon cycle, i.e., the process of carbon transfers between different reservoirs such as atmosphere, oceans and land biosphere (Grace, 2004). The literature on the cyclical characteristics of anthropogenic carbon emissions is limited to a few recent works, all addressing the topic only briefly and indirectly. Zerbo and Darné (2019) supply a short characterization of the cyclical properties of carbon dioxide emissions for OECD and BRICS countries during 1960–2014. They apply a difference filter to per capita carbon emissions to extract the "growth" cycle (Harding and Pagan, 2005) and, thus, sketch a chronology of turning points, durations and amplitudes. Employing the same methodology, Churchill et al. (2020) replicate and extend these results on a slightly different sample of countries over the period 1860–2014. Their findings overlap only partially. Within each study, amplitudes of expansions and contractions display similar magnitudes. However, while Zerbo and Darné (2019) find longer expansionary phases, the results of Churchill et al. (2020) point to the opposite. Coggin (2023), focusing on a panel of countries over the 1961–2014 period, employs the MBBQ algorithm (Harding and Pagan, 2002) to identify periods of expansion and contraction in carbon dioxide emissions and to calculate the corresponding average annual percent growth rates. For most countries, it emerges that carbon dioxide emissions grow more during expansions than contractions.

Effective climate policy requires coordination (Nordhaus, 2019) – even better cooperation (Keohane and Victor, 2016) – among international actors. Several studies on the behaviour of multiple carbon emissions mostly investigate their convergence. Results are ambiguous, in that they are sensible to the sample of countries and the econometric approach employed (Pettersson et al., 2013; Payne, 2020). As a recent example, Lee et al. (2023) show that per capita carbon emissions of 30 OECD countries do not get closer over time, revealing significant differences among them. Cyclical synchronization between economic series is one of the most fruitful branches of business cycles research, covering the most disparate geo-economic areas. Economic integration across relatively heterogeneous macroeconomic entities is at the basis of business cycle synchronization, enhancing policy coordination and communal decision making (Gouveia and Correia, 2013). According to Frankel and Rose (1998), the closer are countries in terms of trade, the greater is business cycle synchronization. Anthropogenic carbon emissions possess their own cyclical features just like business cycles, to which they are procyclically linked (Doda, 2014; Azami and Angazbani, 2020; Sarwar et al., 2021). While Cohen et al. (2022) find the relationship between carbon emissions and the business cycle is symmetric, i.e., carbon emissions increase during booms as much as they decrease during falls, the results of Sheldon (2017) and Gozgor et al. (2019) suggest an asymmetric relationship. In light of this link, this work investigates the cyclical characteristics of carbon emissions integrating, on the one hand, the few results already existing in the literature employing a "classical" cycle approach and, on the other hand, providing an original contribution in terms of synchronization analysis of worldwide carbon emission fluctuations.

3. Materials and methods

3.1. Data

The dataset is organized so as to encompass carbon dioxide emissions of sixteen major emitting economies over the post-World War II period, from 1946 to 2021 (76 years). Developed economies consist in the G7 countries (Canada, France, Germany, Great Britain, Italy, Japan, and United States). Developing economies comprise two groups, namely BRICS (Brazil, China, India, Russia, South Africa) and MIST (Indonesia, Mexico, South Korea, Turkey). To stress the relevance of the selected sample, it is worth mentioning that the included areas cover about 70%[1] of global GDP and 73%[2] of global carbon emissions in year 2021. All series are retrieved from the Global Carbon Budget 2022 (Friedlingstein et al., 2022) and are publicly available. Specifically, the analysis employs territorial carbon emissions originating from aggregate industrial processes of fossil fuel oxidation – combustion and chemical oxidation – and carbonate decomposition (e.g., cement production) – taking place within each specific country. Emissions from bunker fuels and international aviation are not included. Data are provided in aggregate form, which makes it not possible to disentangle the various components and analyse them individually. Series on carbon emissions from consumption process, despite publicly available (Peters et al., 2012), have been discarded since they are too short to be analysed (only 21 observations for each country, one for each year in the period 1990–2020). The dataset is built on annual basis, since carbon emission data are seldom recoverable at a lower frequency. Carbon emissions are measured in million tonnes of carbon (MtC) per year.

3.2. Methodology

Carbon emission fluctuations are characterized by inspecting the "classical" cycle, that is, the log-*level* of each series (McDermott and Scott, 2000; Harding and Pagan, 2002), refraining from employing filters. The analysis is implemented in Julia 1.9.4 (https://julialang.org). The adoption of a "classical" framework based on turning points represents a robust way to characterize fluctuations without relying on the presence of oscillations in the data (Kulish and Pagan, 2021). Within this analysis, a phase is defined as the number of years following a turning point until the next one (Harding and Pagan, 2016, p. 89). Specifically, a phase of contraction consists in a sequence of decreases between a peak and a trough, while a phase of expansion in a sequence of increases between a trough and a peak (Cashin and McDermott, 2002). Each complete cycle is, thus, a matter of three turning-points and, thus, two consecutive phases: one expansion and one contraction, or vice-versa. As a preliminary step, each carbon series undergoes a monotonic log-transformation and is pre-multiplied by 100, i.e., $y_t = 100\, ln\,(CO_2)_t$. This allows to express amplitudes in percent terms without altering each series' turning points. Upon these premises, the analytical process is articulated into three consecutive steps. First, peaks and troughs of each series are identified and dated using the MBBQ algorithm (Harding and Pagan, 2002; Engel, 2005), that is, a *modified* versions of the Bry and Boschan (1971, pp. 64–150) algorithm that does not require any smoothing of the input series for locating turning points (Harding and Pagan, 2016, p. 32). Given the annual nature of carbon dioxide series and their closed link to the production process, the algorithm is constrained to detect phases of at least one year and cycles of at least 2 years as suggested by Harding and Pagan (2016, p. 33). The aforementioned

[1] The results are elaborated from "GDP based on PPP, share of world" (International Monetary Fund)https://www.imf.org/external/datamapper/PPPSH@WEO/OEMDC/ADVEC/WEOWORLD (last access 06/02/2023).

[2] The results are elaborated from "Fossil CO_2 emissions by country (territorial)" (The Global Carbon Budget, 2022) https://doi.org/10.18160/gcp-2022 (last access 06/02/2023).

rules are lifted should a fall larger than 15% in carbon emissions happen. Once peaks and troughs are identified, the algorithm attaches a date to them. This step allows to spot specific periods of interest and construct a binary categorical variable Z_t which signals whether a certain point of the series belongs to a phase of contraction ($Z_t = 0$) or expansion ($Z_t = 1$). As it will become clearer in what follows, Z_t represents the crucial element upon which each further analysis is built.

Once the state variable Z_t is obtained, the second step of the analysis consists in computing a few facts capturing the cyclical features of the series as detailed by Harding and Pagan (2001, 2016, pp. 90–94). Each single phase is characterized by its duration, i.e., the number of years between the couple of consecutive turning points which defines that phase, and amplitude, i.e., the difference in y_t measured at the couple of consecutive turning points that define that phase. More specifically, the state variable Z_t is used to compute the average duration and the average amplitude of phases for each stream of carbon emissions. The former statistic takes the form of Equation (1) for contractions and Equation (2) for expansions

$$D_C = \frac{\sum_{t=1}^{T^*}(1-Z_t)}{\sum_{t=1}^{T^*}(1-Z_t)Z_{t+1}} \tag{1}$$

$$D_E = \frac{\sum_{t=1}^{T^*}Z_t}{\sum_{t=1}^{T^*}(1-Z_{t+1})Z_t} \tag{2}$$

To put it another way, average duration is defined as the ratio between the total time a series spends in a specific phase, either contraction or expansion, over the total number of turning points characterizing that phase, i.e., troughs for contractions and peaks for expansions. For each series, the average duration of the cycle $D_{\aleph}$ is defined as the sum of the average duration of contraction D_C and expansion D_E (Harding and Pagan, 2016, p. 91), that is

$$D_{\aleph} = D_C + D_E \tag{3}$$

Equation (4) and Equation (5) respectively describe in mathematical fashion how to compute the average amplitude of contractions and expansions.

$$A_C = \frac{\sum_{t=1}^{T^*}(1-S_t)\Delta y_t}{\sum_{t=1}^{T^*}(1-S_t)S_{t+1}} \tag{4}$$

$$A_E = \frac{\sum_{t=1}^{T^*}S_t\Delta y_t}{\sum_{t=1}^{T^*}(1-S_{t+1})S_t} \tag{5}$$

Average amplitude is defined as the ratio between total approximate changes in output of a specific phase over the total number of turning points characterizing that phase. It is worth underlying that the characterization of phases, both in terms of duration and amplitude, is carried out only on complete phases, that is to say, by excluding the incomplete phases at the start and at the end of the sample. This translates into using an appropriate sub-sample of length $T^* < T$, where T refers to the length of the full sample.

The third and final step consists in testing whether pairs or groups of carbon dioxide emissions are synchronized. Limiting the explanation to the pairwise case, the hypothesis of no synchronization is expressed as $H_0 : \rho = 0$, where ρ is the sample correlation between the binary state variables of two different countries. In the literature (e.g., Male, 2011; Adarov, 2023), this step is usually achieved by computing the OLS regression of a first state variable Z_{yt} on a second state variable Z_{xt}, and assessing whether the coefficient relating them is significantly different from zero using heteroskedasticity and autocorrelation-consistent (HAC) standard errors. In this work, however, sample correlation ρ is estimated using the generalized method of moments (GMM)[3]; in particular, a test statistic appositely developed by Harding and Pagan (2006, pp. 69–70) is employed, which supplies a consistent estimate of the covariance matrix in Newey and West (1987) fashion in order to account for serial correlation.[4] In general, the test statistic follows a χ^2 distribution with $0.5n(n-1)$ degrees of freedom, where n is the number of series which are to be tested. The degree of synchronization between pairs of series is, finally, assessed using the concordance index (Harding and Pagan, 2002, 2006, 2016, p. 113–115) defined as

$$\widehat{C} = \frac{1}{T}\left[\sum_{t=1}^{T} Z_{xt}Z_{yt} + \sum_{t=1}^{T}(1-Z_{xt})(1-Z_{yt})\right] \tag{6}$$

and signalling the fraction of time binary state variables Z_{xt} and Z_{yt}, i.e., the proxies for the carbon emission cycles of two distinct countries, find themselves in the same phase. Contrary to the characterization of phases and cycle, the synchronization analysis is performed over the whole binary state vector Z_t, that is, by including also those incomplete phases at the extremes of the sample. Each state vector is, thus, considered at its full length so as to make use of as much information as possible about the mutual behaviour of each pair.

4. Results and discussion

4.1. Descriptive statistics

Prior to any cyclical characterization, summary statistics – sample means and sample standard deviations – of raw carbon emissions and their approximate percent changes (i.e., first-differences of log-transformed series) are reported for each country. These results are shown in Table 1. United States and China are, on average, the largest absolute carbon emitters. As highlighted by Zerbo and Darné (2019), United States are, on average, also the largest carbon emitters in per capita terms, while this does not hold for China. China's raw carbon emissions, in particular, present a substantial degree of dispersion. Developing countries such as India, China, Indonesia and South Korea show large average approximate percent changes and variability. These results resemble those of Coggin (2023), who finds India, China, Indonesia, and South Korea to score the highest average annual percent growth rates.

4.2. Characterization of carbon emission fluctuations

Table 2 conveys the characterization of carbon dioxide emission fluctuations in terms of a few meaningful statistics: the number of complete cycles, the time each series spends in contraction measured in percent terms, average durations expressed in number of years, and average amplitudes measured in percent terms. Average amplitudes, in particular, can be interpreted as the approximate percentage change of carbon emission fluctuations within a certain phase. The results are organized by country, phase – either expansion (E) or contraction (C) –

[3] More precisely, in the pairwise case three parameters are estimated: the sample means of the first and second binary state variables and the pairwise sample correlation between the two of them. Since the number of moment conditions equals the number of parameters to estimate, the methodology reduces to a simple method of moments (MM). The logic behind this procedure is easily generalizable to the multivariate case simply accounting for all potential correlations occurring among the series under consideration.

[4] The algorithm makes use of the Moore-Penrose pseudoinverse (Moore, 1920; Penrose, 1955) to approximate the inverse of the variance-covariance matrix of moment conditions employed in GMM estimation.

Table 1
Descriptive statistics of raw and first-differenced log carbon emissions.

Area	Country	Raw Series (MtC)		Percent Change (%)	
		Mean	Std. Dev.	Mean	Std. Dev.
G7	**CAN**	108.99	42.07	1.83	3.98
	DEU	237.05	50.46	1.21	5.33
	FRA	101.26	24.54	0.82	5.59
	GBR	149.78	20.11	−0.31	3.94
	ITA	84.57	40.65	3.60	8.23
	JPN	226.26	118.31	4.01	7.36
	USA	1227.99	326.85	1.06	4.55
BRICS	**BRA**	59.14	44.93	5.58	12.49
	CHN	888.23	953.40	7.68	13.21
	IND	198.89	212.16	5.27	3.15
	RUS	404.18	157.87	2.57	5.49
	ZAF	72.77	39.96	2.74	4.67
MIST	**IDN**	51.73	52.70	8.18	23.62
	KOR	67.94	64.56	9.52	11.85
	MEX	69.98	45.84	3.69	5.58
	TUR	40.21	36.80	5.54	5.59

Notes.
CAN: Canada; DEU: Germany; FRA: France; GBR: Great Britain; ITA: Italy; JPN: Japan; USA: United States; BRA: Brazil; CHN: China; IND: India; RUS: Russia; ZAF: South Africa; IDN: Indonesia; KOR: South Korea; MEX: Mexico; TUR: Turkey.
MtC stands for Million tonnes of Carbon; % stands for percentage.

and/or cycle (CY) depending on the statistic. For sake of interpretation, numerical outcomes are accompanied by graphs portraying the behaviour of carbon emission of each country. Specifically, Fig. 1 refers to the G7 countries, Fig. 2 to the BRICS countries, and Fig. 3 to the MIST countries. Turning points are highlighted in blue when they are troughs and in red when they are peaks.

On average, developed countries have a greater number of completed cycles than developing ones, 12.9 versus 7.4, respectively. All countries belonging to the G7 group feature at least 10 full cycles during the post-World War II period. Specifically, Germany and France display a relatively “fragmented” cyclical pattern characterized by 15 full cycles each. On the other hand, most developing countries feature less than 10 full cycles. As an example, China and South Korea complete respectively only 5 and 2 cycles, while India represents a limit case, in that it features a unique full cycle. This result reflects itself in the longer cycles experienced by most Asian countries, thus, mirroring the behaviour of “classical” business cycles (e.g., Male, 2011). Independent of the degree of economic development, fluctuations in carbon emissions appear to be mostly an expansionary phenomenon. Carbon emissions of most countries spend less than 50% of time in contraction.

On average, developed countries’ carbon emissions are in contraction 42.4% of time compared to 21.7% for developing countries. This can be observed in Fig. 1, where countries such as Germany, France and Great Britain present marked phases of contraction especially in most recent times. On the other hand, countries such as China, India and South Korea in Figs. 2 and 3 present shorter and almost negligible phases of contraction. Paralleling business cycle literature, most countries feature expansionary phases that last in general more (e.g., Altavilla, 2004; Male, 2011) and display larger amplitudes (e.g., Male, 2011) than their contractionary counterparts. Like in Zerbo and Darné (2019), longer expansionary phases of carbon emission fluctuations are linked to developing countries. The average expansionary phase of the BRICS-MIST developing aggregate is 11.7 years, approximately 3.5 times that of the G7 countries (3.3 years). Three developing countries, in particular, show remarkable average expansionary durations of carbon emission fluctuations: 9.5 years for South Korea, 11.8 years for China, and 55 years for India, the latter lasting from 1965 to 2019. This is reflected in the long average cycles of South Korea, China, and India, which last 10.8, 13.5 and 56 years, respectively. It is worth mentioning that South Korea presents a long incomplete phase of – at least – 51 years between 1947 and 1997. Among G7 countries, Italy presents the longest average phase of expansion of carbon emissions. As captured in Fig. 1, this behaviour is probably driven by to the long expansionary phase Italy experienced during the 1949–1974, namely the Golden Age of the Italian economy (Toniolo, 2013), when Italy was itself a developing

Table 2
Characterization of carbon dioxide emission fluctuations.

Area	Country	Full cycles	Time in contraction (%)	Duration			Amplitude (%)	
		CY	*C*	*E*	*C*	*CY*	*E*	*C*
G7	**CAN**	11	27.8	4.7	1.7	6.4	16.1	−4.6
	DEU	15	55.6	1.9	2.2	4.1	5.3	−6.2
	FRA	15	49.3	2.4	2.2	4.6	10.2	−8.3
	GBR	13	55.1	2.4	2.7	5.1	5.6	−8.9
	ITA	10	32.9	4.9	2.2	7.1	29.3	−7.4
	JPN	12	40.3	3.3	2.1	5.4	22.1	−5.3
	USA	14	36.1	3.3	1.7	5.0	10.7	−6.0
	Average	12.9	42.4	3.3	2.1	5.4	14.2	−6.7
BRICS	**BRA**	9	20.5	6.4	1.5	7.9	50.6	−6.5
	CHN	5	14.5	11.8	1.7	13.5	127.5	−15.4
	IND	1	3.5	55.0	1.0	56.0	293.5	−4.6
	RUS	7	47.5	3.0	2.4	5.4	6.9	−9.4
	ZAF	12	24.7	4.6	1.5	6.1	22.2	−5.1
	Average	6.8	22.1	16.2	1.6	17.8	100.1	−8.2
MIST	**IDN**	12	23.9	4.5	1.3	5.8	41.5	−12.7
	KOR	2	17.4	9.5	1.3	10.8	29.0	−9.5
	MEX	10	23.6	5.5	1.5	7.0	31.6	−5.5
	TUR	9	20	5.3	1.2	6.5	38.9	−3.5
	Average	8.3	21.2	6.2	1.3	7.5	35.3	−7.8
BRICS + MIST	**Average**	7.4	21.7	11.7	1.5	13.2	71.3	−8.0

Notes: CAN: Canada; DEU: Germany; FRA: France; GBR: Great Britain; ITA: Italy; JPN: Japan; USA: United States; BRA: Brazil; CHN: China; IND: India; RUS: Russia; ZAF: South Africa; IDN: Indonesia; KOR: South Korea; MEX: Mexico; TUR: Turkey.

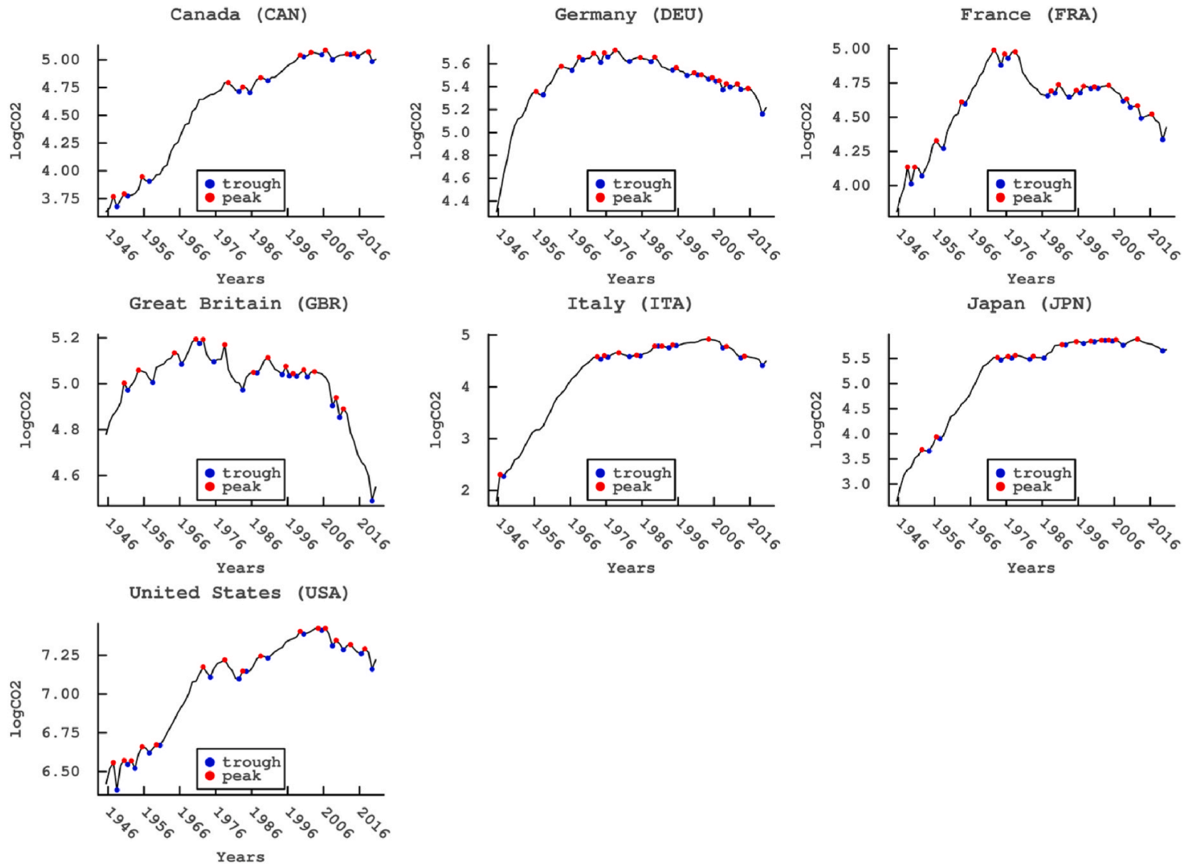

Fig. 1. Peaks and troughs of G7 countries.

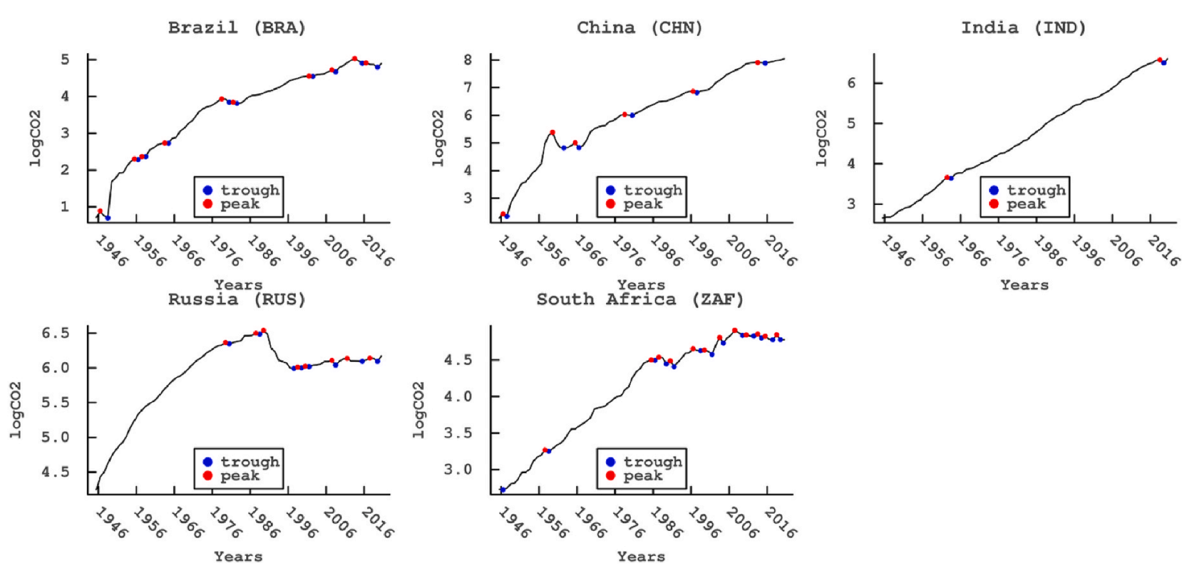

Fig. 2. Peaks and troughs of BRICS countries.

country. Contrary to Zerbo and Darné (2019) and Churchill et al. (2020), where average amplitudes have similar magnitudes during booms and busts, the "classical" framework clearly suggests greater average amplitudes during expansions. Also in this case, the phenomenon is particularly evident for developing countries. The BRICS-MIST developing aggregate, on average, presents an expansionary amplitude of 71.3%, well above the 14.2% of the G7 countries. For example, average amplitude of India's expansionary phases amounts to 293.5%, more than twice that of China, namely 127.5%. Astounding results concerning India and China should not surprise. Their economies rely heavily on fossil energy use and show historically persistent trends in carbon emissions that are very far from stopping (Wang et al., 2020; Ahmed et al., 2023).

On the other side of the spectrum, developed countries such as Germany and Great Britain are characterized by carbon emissions being in contraction more than 50% of the time and featuring contractionary phases relatively longer and deeper than their expansionary counterparts. Specifically, Great Britain's longer contractionary phases emerge

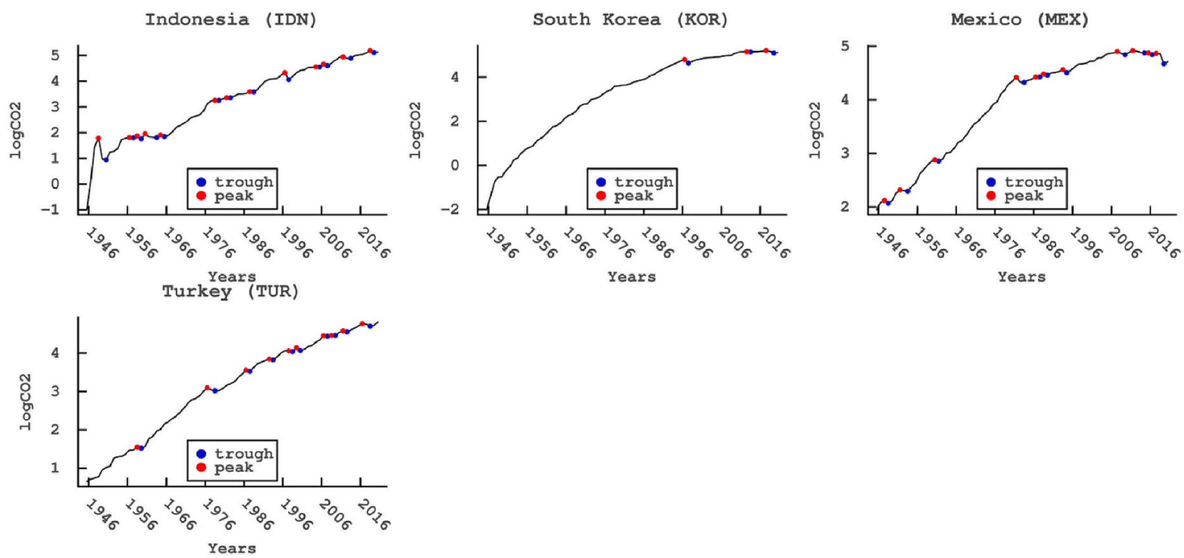

Fig. 3. Peaks and troughs of MIST countries.

also in Zerbo and Darné (2019) and Churchill et al. (2020). This contractionary behaviour can be partially explained by the sustained process of decarbonization driven by the liberalization of energy markets and the coal phase-out (Brauers et al., 2020) in both Germany and Great Britain. Changes in fuel mix, in fact, positively affect the reduction of carbon emissions in *low growth – low emission intensity* countries such as Germany and Great Britain (Duan et al., 2022). Table 5 in the Appendix at the end of the paper presents the dates of all turning points employed in this analysis for each country.

4.3. Synchronization of carbon emission fluctuations

Table 3 deals with the synchronization of carbon emission fluctuations between pairs of countries. Correlations and autocorrelation robust test statistics (in round brackets) are reported below the diagonal; concordance indexes are displayed above the diagonal. The hypothesis of no-synchronization between couples of countries is tested and rejected in 41 out of 120 cases (34.2%). In 19 cases, 12 of them occurring withing the G7 group, the hypothesis of no-synchronization is rejected under the 1% significance level, thereby signalling strong co-movement. This suggests that G7 countries, sharing longer socio-economic histories, would be able to welcome and enjoy higher degrees of carbon policy coordination than other macro-areas. After all, G7 countries – especially those belonging to the EU area – already play a leading role in reducing GHG gases (Zheng et al., 2019). In all other cases, no significant evidence of synchronization is observed. With 9 links each, Italy and Japan share the largest number of synchronized relationships with other countries. Most correlation coefficients appear to be relatively low. If, on the one hand, these values suggest caution for interpretation, on the other, they show magnitudes approximately comparable with those found in similar analyses targeting macroeconomic aggregates such as the industrial production of several countries (e.g., Harding and Pagan, 2006). Carbon emission fluctuations of United States and Canada are the most correlated, $\rho = 0.58$. Those of Great Britain and France ($\rho =$ 0.45), United States and Japan ($\rho =$ 0.45), France and Germany ($\rho =$ 0.47), and Great Britain and Germany ($\rho =$ 0.50) are also remarkable. All above-mentioned pairs belong to G7 and share, to some extent, a certain degree of geographical proximity. Mild countercyclical relations occur between China and Turkey ($\rho =$ -0.17) and China and France ($\rho = -0.20$); these are, however, only weakly significant. Concordance indexes convey reliable information only once synchronization between two series is ascertained. In other words, a high value of concordance index could manifest itself also in the absence of synchronization, thereby potentially leading to ambiguous conclusions (Harding and Pagan, 2016, p. 115). For this reason, only those values linked to synchronized emission fluctuations are truly taken into consideration. Overlapping 95% of time, India and South Korea show the largest degree of concordance between synchronized phases. The phases of United States and Canada agree 82% of the time, thereby confirming the high level of correlation characterizing their relationship. As a counterexample, carbon emissions of pairs such as China and India or China and South Korea, despite sharing the same phase 84% of the time, are not significantly synchronized, which proofs the trickiness behind interpreting the concordance index. Usually, similar contradictory results can arise in cases characterized by very strong expansionary components (Harding and Pagan, 2016, p. 115).

In last instance, the hypothesis of no multivariate synchronization between carbon emissions originating from countries belonging to common economic areas, namely G7, BRIC and MIST, is tested and results are presented in terms of Table 4.

As previously suggested by the pairwise correlation analysis, carbon emission fluctuations of G7 countries appear to be strongly correlated, thereby suggesting a common carbon emission cycle. The multivariate synchronization test produces discordant conclusions when the focus shifts to developing economic areas. While carbon emissions from BRICS appear to be significantly synchronized, this does not hold for MIST countries. The result concerning BRICS countries is interesting, in that they present a common carbon emission cycle despite a relatively recent history of cooperation, heterogeneous geographical locations and socio-cultural features (Zheng et al., 2019).

5. Conclusions

Being descriptive in its character, this paper provides academics and policy makers with general macro-facts, whose knowledge might help predicting booms and busts in carbon emission fluctuations and shaping effective climate policies targeting heterogeneous macro-economic areas such as G7, BRICS and MIST. The result is a new pattern of turning points and, thus, a new perspective on carbon emission fluctuations both in terms of characterization and synchronization. Mirroring business cycle literature, carbon emission fluctuations take the form of a predominantly expansionary phenomenon. Compared to developed countries, developing countries feature on average longer cycles (i.e., a lower number of full cycles), less time spent in contraction, longer expansionary phases, shorter contractionary phases and larger amplitudes in absolute terms. This suggests that BRICS and MIST countries

Table 3
Pairwise synchronizations of carbon emission fluctuations.

	CAN	DEU	FRA	GBR	ITA	JPN	USA	BRA	CHN	IND	RUS	ZAF	IDN	KOR	MEX	TUR
CAN		0.54	0.62	0.58	0.71	0.75	0.82	0.72	0.66	0.74	0.64	0.61	0.67	0.74	0.67	0.63
DEU	0.05 (0.22)		0.74	0.75	0.64	0.63	0.54	0.58	0.51	0.54	0.66	0.59	0.53	0.59	0.53	0.51
FRA	0.23** (4.07)	0.47*** (18.18)		0.72	0.67	0.66	0.62	0.58	0.46	0.54	0.58	0.51	0.53	0.57	0.55	0.54
GBR	0.18 (2.16)	0.50*** (39.15)	0.45*** (21.36)		0.66	0.62	0.63	0.59	0.50	0.50	0.62	0.53	0.51	0.53	0.57	0.53
ITA	0.30*** (8.34)	0.28** (6.24)	0.34*** (9.33)	0.34*** (14.26)		0.72	0.71	0.70	0.63	0.68	0.72	0.58	0.62	0.71	0.64	0.66
JPN	0.43*** (14.03)	0.25** (5.66)	0.31** (6.60)	0.25* (3.43)	0.38*** (10.85)		0.75	0.68	0.64	0.64	0.66	0.59	0.63	0.70	0.63	0.62
USA	0.58*** (34.07)	0.06 (0.21)	0.22* (2.86)	0.28*** (7.25)	0.35*** (12.09)	0.45*** (21.62)		0.72	0.66	0.66	0.59	0.58	0.59	0.66	0.67	0.58
BRA	0.23** (6.31)	0.14 (1.16)	0.14 (1.13)	0.23** (4.59)	0.23** (4.71)	0.25** (4.23)	0.34*** (15.94)		0.80	0.80	0.71	0.67	0.66	0.80	0.74	0.70
CHN	−0.06 (0.40)	−0.05 (0.12)	−0.20* (3.00)	0.00 (0.00)	−0.01 (0.02)	0.12 (0.98)	0.13 (1.56)	0.30* (3.15)		0.84	0.72	0.66	0.75	0.84	0.70	0.71
IND	0.09 (0.48)	0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.07 (0.32)	0.05 (0.21)	0.05 (0.23)	0.13 (0.84)	−0.06 (1.59)		0.75	0.74	0.80	0.95	0.78	0.82
RUS	0.07 (0.30)	0.32*** (8.47)	0.14 (1.79)	0.27*** (6.84)	0.33*** (11.94)	0.21* (3.08)	0.03 (0.08)	0.17 (1.82)	0.13 (1.05)	0.09 (0.54)		0.70	0.66	0.80	0.71	0.67
ZAF	−0.02 (0.03)	0.17 (1.84)	−0.01 (0.01)	0.06 (0.28)	−0.02 (0.03)	0.06 (0.23)	0.01 (0.01)	0.08 (0.46)	−0.06 (0.34)	0.09 (0.50)	0.21*** (7.21)		0.62	0.74	0.70	0.71
IDN	0.11 (0.97)	0.01 (0.01)	0.01 (0.01)	0.03 (0.09)	0.04 (0.17)	0.13 (1.41)	0.01 (0.01)	−0.03 (0.06)	0.16 (1.66)	0.31* (2.75)	0.05 (0.19)	−0.03 (0.13)		0.80	0.68	0.70
KOR	0.13 (1.56)	0.26* (3.40)	0.14 (1.65)	0.12 (1.27)	0.22** (4.22)	0.32** (4.12)	0.08 (0.33)	0.18 (1.37)	0.08 (0.28)	0.33* (2.97)	0.41** (4.53)	0.13 (1.52)	0.30*** (10.93)		0.80	0.82
MEX	0.11 (1.42)	0.01 (0.02)	0.07 (0.65)	0.16 (2.02)	0.11 (0.94)	0.13 (1.36)	0.21* (3.35)	0.21** (4.43)	−0.02 (0.08)	0.11 (0.68)	0.20 (1.97)	0.18 (2.22)	0.09 (0.62)	0.30*** (6.65)		0.72
TUR	−0.09 (1.05)	−0.04 (0.09)	0.03 (0.07)	0.07 (0.39)	0.09 (0.86)	0.06 (0.25)	−0.08 (0.77)	−0.03 (0.08)	−0.17* (3.00)	−0.07 (1.65)	−0.00 (0.00)	0.15 (1.59)	0.03 (0.07)	0.06 (0.33)	0.11 (1.22)	

Notes.
1. *P < 0.1; **P < 0.05; ***P < 0.01.
CAN: Canada; DEU: Germany; FRA: France; GBR: Great Britain; ITA: Italy; JPN: Japan; USA: United States; BRA: Brazil; CHN: China; IND: India; RUS: Russia; ZAF: South Africa; IDN: Indonesia; KOR: South Korea; MEX: Mexico; TUR: Turkey.

Table 4
Multivariate synchronizations of carbon emission fluctuations.

Area	Degrees of freedom	W-Statistic
G7	21	490.76***
BRICS	10	35.06***
MIST	6	7.31

Notes: *P < 0.1; **P < 0.05; ***P < 0.01.

might still fall behind G7 countries along the path to reduce carbon emissions. The evidence of common carbon emission cycles for G7 and BRICS, respectively, suggest these areas could benefit from a higher degree of climate policy coordination.

CRediT authorship contribution statement

Massimiliano Calvia: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset employed in this work is publicly available at https://doi.org/10.18160/gcp-2022 (Friedlingstein et al., 2022)

Appendix

Table 5 provides the list of turning points that characterizes carbon emission fluctuations for each country considered throughout this work.

Table 5
Turning points of carbon dioxide emissions

Area	Country	Turning point typology	Turning point location in time (years)															
G7	**CAN**	*Peak*	1948	1951	1956	1980	1984	1989	2000	2003	2007	2013	2015	2019				
		Trough	1949	1952	1958	1983	1986	1991	2001	2006	2009	2014	2016	2020				
	DEU	*Peak*	1957	1964	1969	1973	1976	1979	1986	1990	1996	2001	2003	2006	2008	2010	2013	2016
		Trough	1959	1967	1970	1975	1977	1983	1989	1995	1999	2002	2005	2007	2009	2011	2014	2020
	FRA	*Peak*	1949	1951	1957	1964	1973	1976	1979	1989	1991	1996	1998	2001	2005	2010	2013	2017
		Trough	1950	1953	1959	1965	1975	1977	1988	1990	1994	1997	2000	2002	2009	2011	2014	2020
	GBR	*Peak*	1951	1955	1965	1971	1973	1979	1987	1991	1996	1998	2001	2004	2010	2012		
		Trough	1952	1959	1967	1972	1976	1984	1988	1995	1997	1999	2002	2009	2011	2020		
	ITA	*Peak*	1947	1974	1976	1980	1985	1990	1992	1995	2005	2010	2015					
		Trough	1948	1975	1977	1983	1986	1991	1994	1996	2009	2014	2020					
	JPN	*Peak*	1953	1957	1974	1977	1979	1984	1992	1996	2000	2003	2005	2007	2013			
		Trough	1955	1958	1975	1978	1983	1987	1993	1998	2001	2004	2006	2009	2020			
	USA	*Peak*	1948	1951	1953	1956	1960	1973	1979	1984	1989	2000	2005	2007	2010	2014	2018	
		Trough	1949	1952	1954	1958	1961	1975	1983	1985	1991	2001	2006	2009	2012	2017	2020	
BRICS	**BRA**	*Peak*	1947	1956	1958	1964	1979	1982	2002	2008	2014	2017						
		Trough	1949	1957	1959	1965	1981	1983	2003	2009	2016	2020						
	CHN	*Peak*	1947	1960	1966	1979	1997	2014										
		Trough	1948	1963	1967	1981	1998	2016										
	IND	*Peak*	1963	2019														
		Trough	1964	2020														
	RUS	*Peak*	1980	1988	1990	1999	2001	2008	2012	2018								
		Trough	1981	1989	1998	2000	2002	2009	2016	2020								
	ZAF	*Peak*		1958	1986	1988	1991	1997	2000	2004	2008	2011	2014	2016	2019			
		Trough	1947	1959	1987	1990	1992	1999	2002	2005	2010	2013	2015	2018	2020			
MIST	**IDN**	*Peak*	1949	1957	1959	1961	1965	1979	1982	1988	1997	2005	2007	2012	2019			
		Trough	1951	1958	1960	1964	1966	1980	1983	1989	1998	2006	2008	2014	2020			
	KOR	*Peak*	1997	2013	2018													
		Trough	1998	2014	2020													
	MEX	*Peak*	1948	1952	1961	1982	1987	1989	1994	2008	2012	2016	2018					
		Trough	1949	1954	1962	1984	1988	1990	1995	2010	2015	2017	2020					
	TUR	*Peak*	1959	1977	1987	1993	1998	2000	2007	2009	2012	2017						
		Trough	1960	1979	1988	1994	1999	2001	2008	2010	2013	2019						

Notes: CAN: Canada; DEU: Germany; FRA: France; GBR: Great Britain; ITA: Italy; JPN: Japan; USA: United States; BRA: Brazil; CHN: China; IND: India; RUS: Russia; ZAF: South Africa; IDN: Indonesia; KOR: South Korea; MEX: Mexico; TUR: Turkey.

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