Title:

Cyclical convergence in per capita carbon dioxide emission in US states: A dynamic unobserved component approach

Abstract:

In this paper we evaluate whether the US states have been able to achieve convergence in their carbon emission cycles which may be a key factor in taking a leap as regards the development of a US climate change policy. The use of a dynamic unobserved component approach and a time-varying parameter model makes possible to estimate the short run dynamics of energy convergence over the extended period 1960-2017. This type of analysis has not received enough attention in the literature so far. The results reveal the existence of cross-state links in the fluctuations of CO_2 emissions, although the degree to which a good part of the states are co-moving is weak. We also find that cyclical convergence patterns differ considerably in both the level and trajectories across the US states. The difficulties in increasing synchronization of the US CO_2 emissions highlight the importance of the states to lead climate change mitigation actions. The present study offers valuable information about the short-run characteristics in carbon dioxide emissions of interest for better understanding the effectiveness of mitigation policies.

JEL: C38, E32, Q51

Keywords: CO_2 emissions, dynamic unobserved component model, factor model, cyclical convergence, Climate change policy.

Nomenclature

- AR: autoregressive
- CDIAC: Carbon Dioxide Information Analysis Center
- CEQ: Council on Environmental Quality
- CERCLA: Comprehensive Environmental Response, Compensation, and Liability Act
- CO_2: Carbon Dioxin
- COPs: Conference of the Parties
- DFA: dynamic factor analysis
- DFM: dynamic factor model
- EIA: U.S Energy Information Administration
- EISA: Energy Independence and Security Act
- EPA: U:S. Environmental Protection Agency
- FRED: Federal Reserve Economic Data
- GFC: Global Financial Crisis
- GHG: Green House Gas
- GMM: General Method of Moments
- HGL hydrocarbon gas liquids
- KSS: Based on the nonlinear unit root test proposed by Kapetanios, Shin and Shell
- LM: Lagrange Multiplier
- NAAQS: National Ambient Air Quality Standards
- NBER: National Bureau of Economic Research
- NCD: National Determined Contributions
- NEPA: US National Environmental Policy Act
- OLS: Ordinary Least Square
- pc: per capita
- PPS: Renewable portfolio standards
- PSD: Prevention of Significant Deterioration
- RALS-LM: Residual Augmented Least Squares-Lagrange Multiplier
- RGGI: Regional Greenhouse Gas Initiative
- SEDS: State Energy Data System
- SO_2 Sulfur dioxide
- SPSM: sequential panel selection method
- UNFCCC: United Nations Framework Convention on Climate Change
- VAR: vector autoregressive

1. Introduction

The US national determined contribution (NDC)[1] is one of the most ambitious commitments in GHGs emissions reduction. Even though the US considered not ratified the landmark agreement at COP21, there has been political support surrounding the importance of a country´s own climate mitigation commitment. The federal government has not been able so far to successfully formulate a national climate change policy that includes a mechanism to reduce CO_2 emissions, but over the last decades policies, regulations, and initiatives have been developed to help improve environmental conditions (Table 1). Moreover, some of the US states have launched several environmental programs to mitigate CO_2 emissions, which the rest are progressively joining. One of the main state-level climate actions is the United States Climate Alliance, a bipartisan coalition to reduce greenhouse gas emissions consistent with goals of the Paris Agreement and in which each state has set its own GHG emissions-reduction targets.

In evaluating the possibilities of the US to achieve the mitigation commitment and advance in the development of a national climate change policy, it becomes clear that it is not only important that national CO_2 emissions be reduced significantly but also per capita emissions should gradually move toward further convergence across US states. The research on energy convergence builds on the literature on economic growth convergence. [2] This field has specifically addressed the dynamics of per capita emissions, and whether CO_2 emissions show evidence of converging trends in the sense that economies with lower initial per capita emission level are experiencing higher emission growth and hence "catching up" with the more intense economies. This has resulted in a rich body of literature examining convergence in energy-related variables. However, these studies have implicitly adopted a long-run perspective [3] and no attention has been devoted to the short run dynamics of energy convergence. The short-term dynamics implies study of the synchronization of the cycles, the cyclical convergence.

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[1] In the Paris agreement, parties were requested to propose "National Determined Contributions" (NDCs) to CO_2 emissions mitigation based on country specific circumstances. The US has proposed to mitigate economy-wide GHG emissions by 26 percent below 2005 levels by 2025 and to make best efforts to reduce emissions by 28 percent by 2025.

[2] A detailed description of the different concepts of economic convergence and various testing methods can be found in Islam [1].

[3] See Acar et al., [2] and Payne, [3], for recent literature review.

Synchronization of emission cycles means similar movements of the countries´ growth rates over time. [4] In this analysis, the countries or regions with strong links in their cycles should bear a lower cost when they implement common policies than those with less synchronized cycles. Synchronization of growth rates clearly can be a factor affecting the CO2 mitigation policies adopted. [5] Such a study should be a valuable complement to the works on the convergence characteristics in carbon dioxide emissions. [6]

The main purpose of this paper is thus to explore cyclical convergence in per-capita CO_2 emissions across US States to show it´s importance in the evaluation of the possibilities of a national climate change policy for the US. With this aim, the contribution is twofold. First, we assess the carbon emission cycle of the 50 US states (excluding District of Columbia). This type of analysis is constrained by the requirement of obtaining an as-long-as possible series. There is no database so far available that contains emissions information for over 50 years. Studies on CO_2 emissions by states usually use data from the US Energy Information Administration (EIA) or from the Carbon Dioxide Information Analysis Center (CDIAC). In order to obtain a database making it possible to carry out the objectives of this research, we consider the possibility of splicing both data sources and thus extend the series from 1960 to 2017.

Then, by using a dynamic unobserved component approach, we allow the data to reveal the states that follow a common cyclical emission pattern, without imposing any functional form on the model. The most suitable analysis in this dynamic multivariate context is the dynamic factor analysis (DFA), since in the short-run, it allows study of similarity of business cycles and their degree of synchronization[7]. The main advantage of these models is that they allow the researcher to characterize the synchronization and co-

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[4] The interest of business cycles synchronization is implied in contributions by Alesina and Barro [4], among others.

[5] In this paper we focus on the relevance of synchronization as an important factor in the design of mitigation CO2 policies. Differently, there is a vast literature that centers on drivers of CO2 generation using different decomposition and panel data techniques. Results show that these factors play different roles during different stages of economic development (Andreoni &Galmarini [5], Inglesi-Lotz[6] y Zhang &Chiu [7].

[6] So far, most of the papers that study the cyclicality and fluctuations patterns of carbon emission dedicated to study the effects of the business cycles on energy variables (Shahiduzzamen and Layton, [8], Khan et al., [9], Gozgor et al., [10] and the role of energy markets as a coordinating mechanism for emission fluctuations McKitrick and Wood, [11]).

[7] We can find other papers that capture the short-run dynamics of the variables but they have the aim to forecasting CO2 emissions (Pao et al., [12] y Wu et al.,[13]).

movement across economies without making strong a priori assumptions. Next, we present a time-varying parameter model proposed in Andrews [14] to test parametrically the dynamics of cyclical convergence. The information about the co-movements in state CO_2 emissions allows us to evaluate the degree and evolution of the cyclical convergence over five decades. This parametric approach offers the significant test of correlation alongside the sample, which is not usually conducted. Also, we applied the robustness check proposed in Cendejas et al., [15], to observe changes in the participation of the countries in the synchronized pattern over the time period. Finally, this paper provides an analysis of the cyclical characteristics of the US carbon emission cycle in terms of duration, amplitude and intensity, using the Harding and Pagan method [16].

Despite the relevance of all these issues, to the best of our knowledge, the estimation of cyclical convergence in carbon dioxide emissions has not received enough attention in empirical work. The present study offers valuable information about the short-run characteristics in carbon dioxide emissions of interest for the designing of mitigation policies. We intend to characterize the short-run behavior of the CO_2 emissions to test existence of cross-state links in state fluctuations. Cyclical convergence implies that states are not following independent paths in mitigation of CO_2 emissions, but are collectively moving towards a common behavior of environmental performance so that it would be possible to set common goals and implement effective national policies. If the cross-state links were weak, it would be better for each state to set its own goals as the effects of national policies may not be optimal for all the states concerned. [8]

The organization of the paper is as follows. Section 2 provides a brief review of the related literature. Section 3 describes the databases employed and the processing involved in computing our dataset. In this section we also present the econometric methodology used in this paper. Section 4 presents the main results of the analysis, followed by concluding remarks in Section 5.

[8] There is a wealth of literature dealing with the analysis of cycle-growth synchronization. Convergence and synchronization of business and growth cycles are important issues in the efficient formulation of policies (Crowley and Schultz, [17]). Its application has been very extensive in the field of fiscal and monetary policy. In the environmental context, it would be possible to interpret similar movements in CO_2 emissions as either indicating ex ante, the suitability for adopting the same environmental policy or ex post, the fact that the environmental policy has been a major factor in achieving a similar pattern of growth.

Table 1. Federal environmental policies, regulations, and initiatives

President	Period	U.S. Environmental policies, regulations, and initiatives
Richard Nixon (Republican)	20/01/1969 09/08/1974	01/01/1970 ***National Environmental Policy Act*** of 1969 (NEPA). that promotes the enhancement of the environment and established the President's Council on Environmental Quality (CEQ) 15/11/1970 ***Clean Air Act Extension*** "national approach to air pollution control" 02/12/1970 ***Creation US EPA***. This is an Agency to protect Human Health and the Environment: Air, Water & Earth 18/10/1972 ***Federal Water Pollution Control Act Amendments***
Gerald Ford (Republican)	09/08/1974 20/01/1977	16/12/1974 ***Safe Drinking Water Act***. To ensure safe drinking water for the public. 21/10/1976 Resource ***Conservation and Recovery Act***. primary law governing the disposal of solid and hazardous waste
Jimmy Carter (Democrat)	20/01/1977 20/01/1981	09/03/1977 ***Clean Air Act Amendments***. Prevention of Significant Deterioration (PSD) of air quality. 27/12/1977 ***Clean Water Act*** 02/04/1980 ***Superfund*** law is officially known as the ***Comprehensive Environmental Response, Compensation, and Liability Act*** of 1980 (CERCLA). EPA is designed to investigate, and clean-up sites contaminated with hazardous substances
Ronald Reagan (Republican)	20/01/1981 20/01/1989	17/10/1986 ***Superfund Amendments and Reauthorization Act***. 04/02/1987 ***Water Quality Act*** of 1987
George H. W. Bush (Republican)	20/01/1989 20/01/1993	15/11/1990 ***Clean Air Act Amendments***: to address the problems of acid rain, ozone depletion, and toxic air pollution, and to establish a national permit program for stationary sources, and increased enforcement authority 24/10/1992 ***The Energy Policy Act*** was far reaching in impacting electric power deregulation, building codes and new energy efficient products
Bill Clinton (Democrat)	20/01/1993 20/01/2001	18/07/1997: Approved ***National Ambient Air Quality Standards (NAAQS)***, the stronger, more protective air quality standards to further control pollution from ozone and particulate matter (smog and soot) and issued a memo to the EPA regarding implementation of those standards. 12/12/1997 The United States signed the ***Kyoto Protocol***. The Protocol must be ratified before it can take effect. (although he did not submit the treaty to the Senate to be ratified)
George W. Bush (Republican)	20/01/2001 20/01/2009	March of 2001 President Bush ***refused to sign the Kyoto Protocol*** 04/01/2005 ***The Energy Policy Act,*** addresses energy production, including: (1) energy efficiency; (2) renewable energy; (3) oil and gas; (4) coal; (5) Tribal energy; (6) nuclear matters and security; (7) vehicles and motor fuels, including ethanol; (8) hydrogen; (9) electricity; (10) energy tax incentives; (11) hydropower and geothermal energy; and (12) climate change technology. 19/12/2007 ***Energy Independence and Security Act*** (EISA) aims: (1) greater energy independence and security; (2) increase the production of clean renewable fuels; (3)protect consumers; (4) increase the efficiency of products, buildings, and vehicles; (5) promote research on and deploy greenhouse gas capture and storage options; (6) improve the energy performance of the Federal Government; and (7)increase energy security, develop renewable fuel production, and improve vehicle fuel economy. 02/11/2011 ***Clear Skies*** was to use a market-based system by allowing energy companies to buy and trade pollution credits
Barack Obama (Democrat)	20/01/2009 20/01/2017	13/02/2009 ***American Recovery and Reinvestment Act (Recovery Act)***. Providing more than $90 billion in strategic clean energy investments and tax incentives 23/10/2015 ***The Clean Power Plan*** (Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units) 29/08/2016 The United States ***signed the Paris Agreement*** 22/06/2016 ***Toxic Substances Control Act***
Donald Trump (Republican)	20/01/2017	01/06/2017 United States President Donald Trump announced that the ***U.S. would cease all participation in the 2015 Paris Agreement*** Trump administration has sought to increase fossil fuel use and scrap environmental regulations, which it has often referred to as an impediment to business

Fuente: Own elaboration with webs information of EPA historical topics, Clinton & Obama Whitehouse archives: https://www.epa.gov/history/historical-environmental-topics ; https://www.epa.gov/environmental-topics ; https://obamawhitehouse.archives.gov/ ; https://clintonwhitehouse4.archives.gov/CEQ/earthday/ch13.html

2. Background to the U.S. states convergence in energy-related variables

Over the last decades a rich empirical literature investigating convergence of carbon dioxide emissions among countries has been developed. One important motivation for addressing this research topic internationally is that convergence in per capita terms could influence the political economy of negotiating multilateral agreements. If carbon dioxide emissions do converge across countries and over time, there will be less pollution mitigation burden for them, and countries would be more likely to engage in a global climate commitment.

Many of these papers include the US in their analysis as it is one of the most polluting countries. Although the US has very strongly opposed the per capita emissions approach in the international climate negotiations and does not have a national climate change policy, results obtained in a good part of these articles show that it is among the countries that show convergence (Presno et al., [18], Erdogan and Acaravci, [19], Cai et al., [20]). This type of result would support the participation of the US in international agreements, but undoubtedly to understand national behavior of the US emissions, it is also necessary to study convergence across their states. When considering the implementation of a national emission abatement strategy to reduce emissions, the existence of convergence across states would reduce the adjustment costs and redistribution effects that can adversely impact the underlying economic structure of the states.

The convergence characteristics of energy related variables have also attracted attention in studies at subnational level, but still not enough papers have investigated convergence across the US states.[9] Table 3 provides a summary of the recently published articles. In these empirical research different energy related variables mainly from the databases EIA and CDIAC have been employed. Among them, CO_2 emissions have attracted great interest in convergence analysis. Aldy [21] examines cross-section and stochastic convergence using estimates of per capita CO_2 emissions from consumption and production over the period 1960-1999 based on EIA database. The results indicate

[9] Unlike in the US, there is a great number of works undertaken on energy-variables at the subnational level dedicated to the Chinese provinces, cities and households (Li et al.,[22]. Wu et al. [23] and Hao et al., [24]).

divergence with respect to CO_2 emissions from production whereas CO_2 emissions associated with consumption reveal some cross-sectional divergence. Burnett [25] uses data of CO_2 emissions per capita from 1960 to 2010 for the 48 contiguous US states applying the Phillips-Sul club convergence approach. The results reveal the emergence of one convergence club to a unique steady state in the case of 26 states. Apergis and Payne [26] examine per capita CO_2 emissions for the 50 states in the US and the District of Colombia at the aggregate level, by sector and by fossil fuel source using the Phillips-Sul club convergence approach over the period 1980-2013. Their findings reveal multiple convergence clubs at the aggregate level of per capita CO_2 emissions, by sector and two of the three fossil fuel sources. Meanwhile Li et al, [27], employing unit-root tests with a Fourier function to test convergence of CO_2 emissions over the period 1990-2010, find that only 12 of the 50 US states exhibit stochastic convergence.

There are also quite a few studies that focus on CO_2 consumption of the US states. Apergis et al., [28] evaluate energy intensity convergence across the 50 states in the US and the District of Colombia from 1997 to 2013 based on cross-sectional test on beta and sigma convergence and find support for overall convergence. However, panel unit root tests with allowance for cross-sectional dependence and structural breaks do not yield support for stochastic convergence. Burnett and Madariaga [29] extends a neoclassical growth model to examine the implications for convergence in economic growth and energy intensity. Using a dynamic panel model estimated with GMM framework they evaluate energy intensity convergence over the period 1970-2013. Their results find support regarding convergence across US states. In the case of Payne et al. [30], they examine the stochastic convergence of per capita fossil fuel consumption across the 50 US states (including the District of Columbia) utilizing LM and RALS-LM unit root tests for the period 1970-2013. They offered sufficient evidence to conclude that concerning per capital fossil fuel consumption, 49 US states and the District of Columbia exhibit convergence. Mohammadi and Ram [31], used data of per capita energy consumption from 1970 to 2013 for the 48 contiguous US states and studied five different concepts of, or approaches to convergence. The overall scenario seems to be that of the lack of convergence in per-capita energy consumption across the US states during the period studied, suggesting a certain degree of stability in the state-level distribution of per-capita consumption and the low likelihood of a significant change in the distribution.

Finally, we find the works from Bulte et al, [32] and Payne et al, [33], which have investigated pollution variables relative to the US states, in this case from EPA. Bulte et al, [32] explore pollution convergence on two important pollutants – nitrogen oxides and sulfur oxides - using data from 1929 to 1999 for the 48 contiguous US states. They find stronger evidence of converging emission rates during the federal pollution control years (1970-1999) than during the local control years (1929-1969). Meanwhile, Payne et al., [30], examine the stochastic conditional convergence of sulphur dioxide emissions using the residual augmented least squares-lagrange multiplier (RALS-LM) unit root test with structural breaks. The study finds that per capita Sulphur dioxide emissions exhibits stochastic conditional convergence across the 50 US states and the District of Colombia from 1900 to 1998.

Many of these papers focus on understanding whether per capita CO_2 emissions exhibit the properties of stationarity for the analysis of convergence which enforce environmental protection policies in long-run (Apergis et al, [28], Bulte et al. [32]). If per capita CO_2 emissions present the I (1) process, then the policies affecting the emissions will have permanent effects. If per capita CO_2 emission series exhibit an I (0) process, then the effects of the policies are merely transitory. Unlike the above-mentioned papers, the dynamic factor model (DFM) [10] employed in this research allows us to analyze the relationships of the CO_2 emissions in the short-run. We propose study of the common behavior of the state emission cycles, and should these be synchronized, it would imply that national climate change policies could influence the states that follow the common pattern.

[10] It is also possible to use DFM in the long-run, Stock and Watson [34], Peña and Poncela, [35] and González and Nave, [36] made some proposals regarding its use in this context.

Table 2. Overview of empirical papers on convergence in energy related variables across the U.S. states

	Author	Convergence and Econometric Approach	Sample	Target Variables	Data	Empirical findings
CO_2 emissions	*Aldy [21]*	*Cross-sectional test of σ convergence, kernel density and stochastic convergence tests.*	*1960-1999*	*CO_2 emissions pc*	*EIA*	*Divergence with respect to production CO_2 emissions pc and no evidence of convergence for consumption CO_2 emissions pc.*
	Li et al., [27]	*Panel KSS unit root test with a Fourier function through the SPSM procedure*	*1990-2010*	*CO_2 emissions*	*EIA*	*CO_2 emissions only converge in 12 out of the 50 U.S. states.*
	Burnett, [25]	*Phillips and Sul club convergence tests approach and conditional β -convergence.*	*1960 2010*	*CO_2 emissions pc*	*CDIAC*	*Convergence for a group of 26 states. The β -convergence tests for the 26 states club is slightly higher than for the entire sample.*
	Apergis & Payne, [26]	*Phillips and Sul club convergence tests approach*	*1980-2013*	*CO_2 emissions pc*	*EIA*	*The results indicate multiple convergence clubs in the aggregate, by sector, and for natural gas and coal fuel sources.*
CO_2 consumption	*Burnett & M., [29]*	*Augmented Solow growth model estimated using a GMM framework to test conditional convergence.*	*1970-2013*	*Energy intensity*	*EIA*	*Results indicate convergence in energy intensity across the entire sample.*
	Apergis et al., [28]	*Cross-sectional test of β and σ convergence and stochastic convergence using panel unit root tests.*	*1997-2013*	*Energy intensity*	*CDIAC*	*Results lend support for overall β and σ convergence but absence of stochastic convergence.*
	Payne et al., [30]	*Stochastic convergence using LM and RALS-LM unit root test*	*1970-2013*	*Fossil fuel consumption pc*	*EIA*	*Results indicate the presence of stochastic convergence in relative per capita fossil fuel consumption in 49 states.*
	Mohammadi &R. [31]	*Beta, sigma, Kernel density function, gamma convergence and stochastic convergence*	*1970–2013*	*Energy consumption pc*	*EIA*	*The predominant finding is that of lack of convergence in per-capita energy consumption across the US states.*
Pollution	*Bulte et al., [32]*	*Stochastic Convergence & Time Series Test for β-Convergence*	*1929-1999*	*SO_2 & NOx pc*	*EPA*	*Strong evidence of convergence during the federal pollution control years (1970–1999) than during the local control years (1929–1969).*
	Payne et al., [33]	*Stochastic conditional convergence using the RALS–LM unit root test with structural breaks*	*1900–1998*	*SO_2 pc*	*EPA*	*Evidence of conditional convergence across US states.*

Source: Own elaboration.
Notes: RALS-LM (Residual Augmented Least Squares-Lagrange Multiplier); KSS (Based on the nonlinear unit root test proposed by Kapetanios, Shin and Shell); LM (Lagrange Multiplier); CDIAC (Carbon Dioxide Information Analysis Center); EIA (U.S. Energy Information Administration); EPA (US. Environmental Protection Agency); SO_2 (sulphur dioxide); CO_2 (carbon dioxide); SPSM (sequential panel selection method) pc (per capita); GMM (General Method of Moments).

3. Data sources and processing

One of our purposes in this paper is to extend convergence analysis as much as possible over time to expand the evidence and to offer viable solutions to the methodological problem derived from having a large sample of states (50). No database containing emissions information for over 50 years is available. Studies on CO_2 emissions by states usually use the EIA database from 1980 to 2017 or CDIAC from 1960 to 2010. Both databases are based on estimates of CO_2 emissions. This type of measure for emissions is one of the most commonly used in the literature as it is difficult to obtain atmospheric emissions of carbon dioxide. To obtain a dataset covering the period 1960-2017, we consider the possibility of splicing the two databases and extending the sample, incorporating a sufficient timespan to study cyclical convergence. In order to do so, first we need to homogenize the data.

The Carbon Dioxide Information Analysis Center (CDIAC) within the U.S. Department of Energy, estimates annual data emissions from oxidation of natural gas, coal, and petroleum products (Blasing, Broniak, & Marland [37]), by multiplying state-level consumption by their respective thermal conversion factors. The estimates are offered in units of Tera-grams of Carbon for the 50 contiguous states excluding the District of Columbia (http://cdiac.ornl.gov/CO2, Emission/timeseries, accessed 07/06/2017[11]). There are annual data available of aggregate U.S. by States Carbon emissions for the period 1960–2010. The year 2010 is the most recent year regarding CDIAC data available and the disaggregated in Carbon emissions by gas, liquid and solid in carbon units.

More up-to-date data can be accessed from the U.S. Energy information Administration (EIA [38]) that has annual data of total CO_2 emissions at the state level from 1980 to 2017, which is measured in millions of metric tons for each US state (https://www.eia.gov/environment/emissions/state/, accessed 03-01-2020). The emissions estimate at the state level for energy-related CO_2 are based on data in the State Energy Data System (SEDS). The state-level emissions estimates are based on energy

[11] In March 2018 the website had changed, so the CDIAC data files that we have used for the article are no longer available on the website, therefore, we have included this data as annex of this article.

consumption data for fuel types: coal (four categories of coal[12]), natural gas and petroleum (eighteen petroleum products[13]). The information available for each state reveals that emissions of CO_2 are disaggregated in 5 sectors (residential, commercial, industrial, transportation and electric power), and in each sector there are three disaggregated sources (coal, petroleum products and natural gas). Of course, there is an aggregate CO_2 for each state and for the USA (for more details see: [39] https://www.eia.gov/environment/emissions/state/pdf/statemethod.pdf, accessed 03-01-2020).

Then, we find that as to the EIA basis the data for CO_2 emissions are expressed in million metric tons of CO_2. On the other hand, we have the CDIAC data expressed in Tera-grams of Carbon. To convert from carbon to carbon dioxide, multiply by 44/12 (=3.667). At this point we have both databases expressed in the same units.

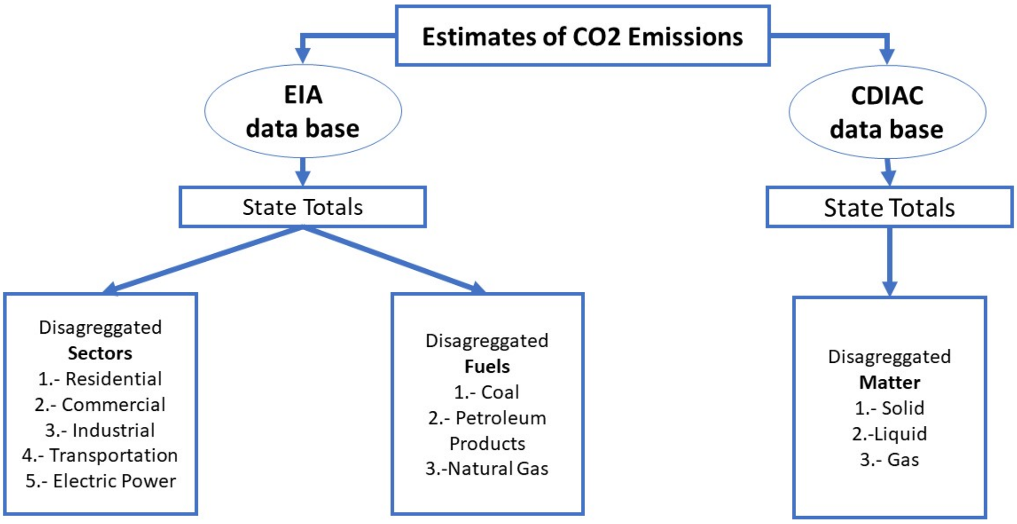

Fig. 1: Estimates of state CO_2 emissions over the period 1960-2017

Source: own elaboration from EIA and CDIAC databases.

We can check discrepancy between both databases by comparing the first and the last year of coincidence of both data bases and analyzing their state data totals. Those years

[12] 1.- residential/commercial sector, 2.- industrial sector coking, 3.- industrial sector & 4.- electric power sector

[13] 1.- asphalt and road oil, 2.-aviation gasoline, 3.-distillate fuel, 4.-jet fuel, 5.-kerosene, 6.-hydrocarbon gas liquids (HGL), 7.-lubricants, 8.- motor gasoline, 9.-petrochemical feedstocks, 10.- petroleum coke, 11.-residual fuel oil, 12.- waxes, 13.-special naphtha, 14.- still gas, 15.- unfinished oils, 16.- miscellaneous products, 17.- natural gasoline, & 18.- other petroleum products.

are 1980 and 2010. Using the expression $\left(\frac{CO2\_IEA_{i,t}}{CO2\_CDIAC_{i,t}}-1\right)\cdot 100$ we calculate the % of discrepancy between both databases and years. [14]

As the discrepancy between the series is minimal, we use a deterministic splicing procedure as proposed in de la Fuente [40]. A simple retropolation works by extending the new series backward from time T, the link point in our case is T=1980, and using a constant growth rate $\frac{CO2\_IEA_{i,1980}}{CO2\_CDIAC_{i,1980}}$, the idea is to "raise" the older series by a constant proportion, respecting its time profile, until it matches the new series at the linking point in order to attenuate the discrepancy.

Annual state population data were obtained from the Federal Reserve Economic Data (FRED). The data available are for the first day of the year ([41] https://fred.stlouisfed.org/release/tables?rid=118&eid=259194, accessed: 04-06-2020)

4. Methodology

4.1. Carbon emission cycles.

Our proposal is rooted in the application of business cycle analysis methods and we resort to the synchronization concept to define cyclical convergence. Cyclical convergence implies the increase in the level of similarity between the states CO_2 emissions cycles. To do this, it is necessary to first obtain the cyclical component of the state CO_2 emissions. Accordingly, the annual series on carbon dioxide emissions per capita at the state level have been log-transformed and differentiated ($\Delta = 1 - L$, being L the lag operator) to obtain the state carbon emission cycles. [15]

4.2. Dynamic factor model (DFM).

[14] Only 3 States have ±3% of difference in both years: Louisiana, North Dakota and Washington.

[15] This is the "growth" definition and the one that is most frequently employed in the empirical literature on business cycles. In this case, a recession is usually defined as a period of at least two consecutive years of negative growth. For a discussion of alternative definitions see Prescott and Kydland [42]. Originally, one of the most used approaches was to apply the Hodrick Prescott filter proposed by Hodrick and Prescott [43]. However, this filter has several shortcomings, see Hamilton [44].

The estimation proposed is based on the measurement of the cyclical common factor using a dynamic unobserved component approach. To that end, we model the degree of co-movements in CO_2 emissions using a dynamic factor model in the tradition of Forni and Reichlin [45], Stock and Watson [46] and Forni et al. [47]. According to Stock and Watson [48] the unobserved components model is based on the notion that co-movements in macroeconomic variables have a common element that represents the general state of the economy and can be captured by a single underlying variable.

DFM is based on the assumption that a small number of unobserved latent factors, f_t, generate the observed time series through a stochastically perturbed linear structure. Formally, it is assumed that the pattern of observed co-movements of a high-dimensional vector of time-series states, $X_t = \Delta \ln CO2_{i.t}$ [16], can be represented by few unobserved latent common dynamic factors. The latent factors follow time series processes, which are commonly taken to be a vector autoregressive model (VAR). DFM can be summarized as:

$$\begin{aligned} X_t &= \Lambda f_t + e_t \\ f_t &= \psi(L) f_{t-1} + \eta_t \end{aligned} \tag{1}$$

where there are N states, so X_t and e_t are $N\times1$; there are m dynamic factors, so f_t and η_t are $m\times1$, $\Lambda = (\beta_1, \beta_2, \ldots, \beta_m)$ is $N\times m$, L is the lag operator, and the lag polynomial matrix $\psi(L)$ is $m\times m$. The *i-th* β_i are called factor loadings for the *i-th* countries, that offer the level of participation of each state regarding co-movements captured by the common factor or factors. The idiosyncratic disturbances, $e_t = (e_{1,t}, e_{2,t}, \ldots, e_{N,t})'$, are the specific elements of each series contained in a vector. These elements are serially correlated and slightly cross-sectionally correlated with other variables in the model and mutually uncorrelated at all leads and lags, that is, $Ee_{it}e_{js} = 0$ for all s if $i \neq s$. They are assumed to be uncorrelated with the factor innovations at all leads and lags, that is,

[16] These series are stationary (log-transformed and differentiated) and are assumed to be non-cointegrated. The series are non-cointegrated if the common factor follows an invertible process $MA(\infty)$. Otherwise, the estimate proposed by Peña and Poncela [35] can be used.

$Ee_t\eta'_{t-k} = 0$ for all k. The p_{th} order autoregressive polynomial, $\psi_i(L)$, is assumed to have stationary roots. As we do here, it is common to reduce the number of parameters by estimating the signal-to-noise ratios $q_{i,m} = \frac{\sigma^2_{\eta,i}}{\sigma^2_{e,i}}$ (Harvey and Trimbur, [49]).

For that purpose, in this paper we use the GROCER's Econometric Toolbox (Dubois and Michaux, [50]). The standard estimation method is maximizing the likelihood of the corresponding model and estimation accuracy via the Kalman filter[17] after a suitable reparameterization of the model in state-space form, assuming that all the processes in (1) are stationary and not cointegrated.

We can confirm the existence of common factors, $\hat{f}_{CO2,t}$, by employing the statistical criterion proposed by Bai and Ng [51])[18]. If we obtain only one common factor, this factor can represent the US cyclical performance of CO_2 emissions. For a better identification of this fluctuation pattern, we also employ the Harding and Pagan [16] dating method. This method enables us to examine the turning points of the US cyclical performance of CO_2 emissions and to estimate their characteristics of duration, amplitude and intensity.

4.3. A time-varying parameter model.

The study of the dynamics in the cyclical behavior of the national CO_2 emissions enables assessment of the trajectory of the cyclical convergence of the states. In line with this objective, we propose the use of a time-varying parameter model presented in Andrews [14] to test parametrically the degree of cyclical convergence of the US states with respect

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[17] A detailed description of the Kalman filter can be found in Clark [52], and Stock and Watson [46].
[18] The number of dynamic factors, p, following Bai and Ng [51] is $p \leq r$, being r the number of static Factors determined by Bai and Ng [53], where $p = 1$ since $r = 1$ according to the following criteria:

$$IC_{pl}(q) = \log(\det(\Sigma)) + q\frac{(N+T)}{nT} + \log\left(\frac{nT}{N+T}\right)$$

$$IC_{pl}(q) = \log(\det(\Sigma)) + q\frac{(N+T)}{nT} + \log(\min(n,T))$$

$$IC_{pl}(q) = \log(\det(\Sigma)) + q\frac{\log(\min(n,T))}{(\min(n,T))}$$

Where Σ = *variance matrix of residual* e_t.

to the cyclical common factor throughout the time period. Accordingly, we recursively estimate:

$$x_{j,t} = \beta_j(\tau)\hat{f}_{CO2,t} + v_{j,t}(\tau) \tag{2}$$

where $x_{j,t}$ is the *j-th* observed series –stationary transformed and standardized- and $\hat{f}_{CO2,t}$ the estimated common factor at *t*. $\beta_j(\tau)$ corresponds with the factor loadings or correlations between each of the *j* series and the common factor. [19] The error term $v_{j,t}$ may include non-significant dependence on discarded factors or maybe specific variation of $x_{j,t}$. In both cases, $v_{j,t}$ must be uncorrelated with the regressors –retained factors- for consistent OLS estimation of (1) and (2), so previous factor estimation must be subject to the appropriate orthogonality conditions. Nevertheless, it is assumed that the error term in (1) can generally show both heteroskedasticity and autocorrelation, thus consistent OLS standard error estimates of $\beta_j(\tau)$ must be robust to both assumptions.

This procedure allows us to extract information about the recursive correlations along the time period studied and offer graphic information on their evolution as a continuum of results and their t-statistics. From said results it is possible to analyze how the states are synchronizing their emissions cycles over the years studied (as it is standard in literature, we consider that the correlation is high if β_j takes on values >0.5). Additionally, we strive to solve part of the possible limitations of our results, confirming the stability of the parameters and verifying the non-existence of structural breaks. To this end, we applied the robustness check proposed in Cendejas et al., [15], to observe changes in the participation of the countries in the synchronized pattern over the time period.

5. Empirical results.

5.1. Results of the synchronization of US States cycles.

[19] The degree of synchronization will be measured by the number of leading or lagging periods at which the maximum correlation is obtained so that, state emissions *i* will be synchronized with the US fluctuation pattern if the maximum correlation is obtained contemporaneously.

As a first step in our analysis, we measured the carbon emission cycle of the states. The results are presented in Figure A1 of Annex. From this information, DFM specified in (1) is estimated for the entire sample period from 1961 to 2017. The parameters of the estimated model are reported in Table 3. The AR idiosyncratic parameter and noise ratio confirm the suitability and dynamics of the model.

Table 3 offers the information of the states ranked according to their factor loadings. The significance of the factor loadings indicates that state emissions are co-moving and confirm the existence of cross-state links in the fluctuation of the state-O_2 emissions. We find that the factor loadings are significant and statistically similar for 47 out of the 50 states. For Alaska, Rodhe Island and Vermont, factor loadings were not significant and then these states were excluded from the model, which is why they do not appear in the table. Said states follow independent emission fluctuation patterns.

The factor loading obtained parametrically in the estimation are the weights (in correlation) with respect to the cyclical common factor. They offer a measure of the importance of the common fluctuation pattern to explain the state emissions cycles. Based on our results, we can differentiate between states that strongly share the US common fluctuation pattern (in this group we find Pennsylvania, Minnesota, Ohio and Indiana, among others, with factor loadings $\beta_j \geq 0.5$). In this analysis, we also find states with emissions that show weaker linkages ($\beta_j < 0.5$). Such is the case of states like Idaho, South Dakota and Nevada. For these states, national policies to control climate change would have less impact on the cyclical behavior of its fluctuations. Furthermore, we applied the robustness check proposed in Cendejas et al., [15]. The results of the test for structural breaks allow us not to reject the null hypothesis of parameter stability according to the simulated critical values for the period 1961-2017, with the exception of New Mexico. It is also important to note that the stationarity of the factor, confirmed by the invertible MA parameter, implies that the effects of national environmental initiatives on the state emissions could only have transitory effects.

These results show that changes in emissions are more symmetrical in amplitude than duration, reflecting the difficulties for national environmental initiatives to achieve a sustained impact on emissions.

Table 3. Estimation results from model (1). Sample period: 1961-2017

$$f_t = \eta_t + 0.73(2.87***)\eta_{t-1}$$

Rank	Countries	Standardized factor loadings	AR parameters	Residual variance
1	Pennsylvania	0.64 (7.96)***	0.02 (0.13)	0.27 (4.96)***
2	Minnesota	0.61 (7.48)***	-0.13 (-0.95)	0.34 (5.08)***
3	Ohio	0.6 (7.84)***	-0.21 (-1.49)	0.28 (5.03)***
4	Indiana	0.6 (7.61)***	-0.15 (-1.12)	0.31 (5.06)***
5	Virginia	0.58 (7.17)***	-0.13 (-0.94)	0.37 (5.12)***
6	Alabama	0.57 (6.92)***	-0.14 (-1.04)	0.41 (5.15)***
7	New York	0.56 (6.73)***	-0.06 (-0.43)	0.45 (5.17)***
8	North Carolina	0.56 (6.58)***	0 (-0.02)	0.44 (5.16)***
9	Michigan	0.56 (6.56)***	-0.19 (-1.44)	0.45 (5.17)***
10	Florida	0.56 (6.56)***	-0.17 (-1.29)	0.48 (5.18)***
11	South Carolina	0.54 (6.72)***	-0.01 (-0.04)	0.48 (5.19)***
12	Maryland	0.54 (6.51)***	-0.28 (-2.09)**	0.45 (5.18)***
13	Wisconsin	0.54 (6.24)***	-0.17 (-1.22)	0.45 (5.18)***
14	Kentucky	0.53 (6.18)***	-0.17 (-1.24)	0.52 (5.21)***
15	Illinois	0.53 (6.13)***	-0.05 (-0.34)	0.5 (5.2)***
16	Georgia	0.51 (6.07)***	0.31 (2.35)**	0.43 (5.17)***
17	Iowa	0.51 (6.03)***	-0.13 (-0.95)	0.5 (5.22)***
18	Texas	0.5 (5.95)***	0.35 (2.71)***	0.43 (5.17)***
19	West Virginia	0.49 (6.16)***	-0.17 (-1.27)	0.52 (5.23)***
20	Tennessee	0.49 (5.9)***	-0.29 (-2.19)**	0.49 (5.22)***
21	Colorado	0.48 (5.75)***	-0.25 (-1.87)*	0.58 (5.24)***
22	Kansas	0.48 (5.27)***	-0.14 (-1.03)	0.58 (5.25)***
23	Missouri	0.47 (5.49)***	0.12 (0.88)	0.57 (5.24)***
24	Montana	0.46 (5.65)***	0.01 (0.05)	0.62 (5.25)***
25	California	0.46 (5.34)***	-0.34 (-2.65)**	0.6 (5.25)***
26	Connecticut	0.46 (5.11)***	-0.19 (-1.44)	0.62 (5.25)***
27	Washington	0.45 (5.41)***	-0.26 (-1.99)**	0.6 (5.25)***
28	New Jersey	0.43 (5.43)***	-0.29 (-2.23)**	0.55 (5.25)***
29	Mississippi	0.43 (5.13)***	-0.32 (-2.49)**	0.66 (5.27)***
30	Hawaii	0.41 (4.72)***	-0.27 (-2.12)**	0.76 (5.28)***
31	New Hampshire	0.41 (4.67)***	0.18 (1.35)	0.63 (5.27)***
32	Louisiana	0.41 (4.54)***	-0.11 (-0.85)	0.71 (5.28)***
33	Nebraska	0.41 (4.5)***	-0.19 (-1.4)	0.67 (5.28)***
34	Massachusetts	0.4 (4.79)***	-0.29 (-2.26)***	0.67 (5.28)***
35	Wyoming	0.39 (4.61)***	-0.28 (-2.19)**	0.69 (5.28)***
36	Oregon	0.36 (4.1)***	-0.16 (-1.23)	0.74 (5.29)***
37	Utah	0.36 (3.86)***	0.16 (1.2)	0.71 (5.29)***
38	Arizona	0.35 (3.7)***	-0.03 (-0.23)	0.78 (5.3)***
39	Delaware	0.34 (3.58)***	0 (0.02)	0.79 (5.3)***
40	Oklahoma	0.34 (3.56)***	0.14 (1.06)	0.77 (5.3)***
41	Arkansas	0.3 (3.3)***	-0.18 (-1.35)	0.81 (5.31)***
42	Nevada	0.29 (2.94)***	0.13 (0.96)	0.83 (5.31)***
43	Idaho	0.27 (2.82)***	0 (0)	0.87 (5.32)***
44	Maine	0.26 (3.13)***	-0.3 (-2.31)***	0.81 (5.32)***
45	North Dakota	0.26 (2.64)***	0.21 (1.63)	0.84 (5.32)***
46	South Dakota	0.21 (2.22)***	-0.11 (-0.79)	0.91 (5.33)***
47	New Mexico	0.21 (2.17)**	-0.14 (-1.05)	0.94 (5.33)***

In () t-statistics, * significant parameter at 90%, ** at 95% and *** 99%.

Note: Using the test proposed in Cendejas et al., [15], we have not detected dates of structural breaks, confirming the stability of parameters' model (1), with the exception of New Mexico with a structural break in 1977.

Once the relationship of the cross-states cycle correlation is summarized in the cyclical common factor, we are able to provide an analysis of its properties based on the dating methodology from NBER.[20] Figure 2 shows the evolution of the US cyclical performance from 1961 to 2017. We can observe that fluctuations of emissions are longer and steeper in the period 1961-1990 (before the United Nations Framework Convention on Climate Change (UNFCCC) 1992, and the subsequent Kyoto Protocol 1997 took place) than in the second period 1991-2017. During the first three decades studied, we identify a phase from peak to trough (1970-1982) where a decline in the growth emissions occurs from the time the Clean Air Act of 1970 was introduced in the US to enhance energy conservation, improve energy efficiency, and promote the use of renewable energy. The economic expansion of the 80s gives rise to the start of another phase of increase in emission growth during the years 1982-1988 (from trough to peak). The start of the UNFCC and the Conference of Parties (COPs) negotiations marks the beginning of the next period characterized by a greater control over emissions fluctuations and of more stable growth rates. The approval of the Energy Policy Act in 1992, extended in 2005, and the Energy Independence and Security Act in 2007 are also some of the federal initiatives launched in this period. However, the financial crisis, gives rise to a new phase of increasing in the rate of growth of the emissions from 2009.

Upon comparing the cyclical characteristics in the different phases, we observe that the average duration of the period of increase in emissions (6 years) are shorter than that of decline in emissions (17.5 years), with an average amplitude of the increase (4.16) similar to the decline (-3.73). This difference in durations implies a greater average intensity[21] of emissions in decline (0.7) than in increase (0.21), as can be observed in 1974, 1980, 1989, 2008 and 2011 troughs, versus 1982, 1988 and 2010 peaks. These results show that changes in emissions are more symmetrical in amplitude than duration, reflecting the difficulties for national environmental initiatives to achieve a sustained impact on emissions.

[20] Available at https://www.nber.org/cycles.html

[21] Intensity is a concept that jointly analyzes the amplitude and duration of a phase, $\frac{amplitude}{duration}$, providing an additional interpretation of expansions and recessions.

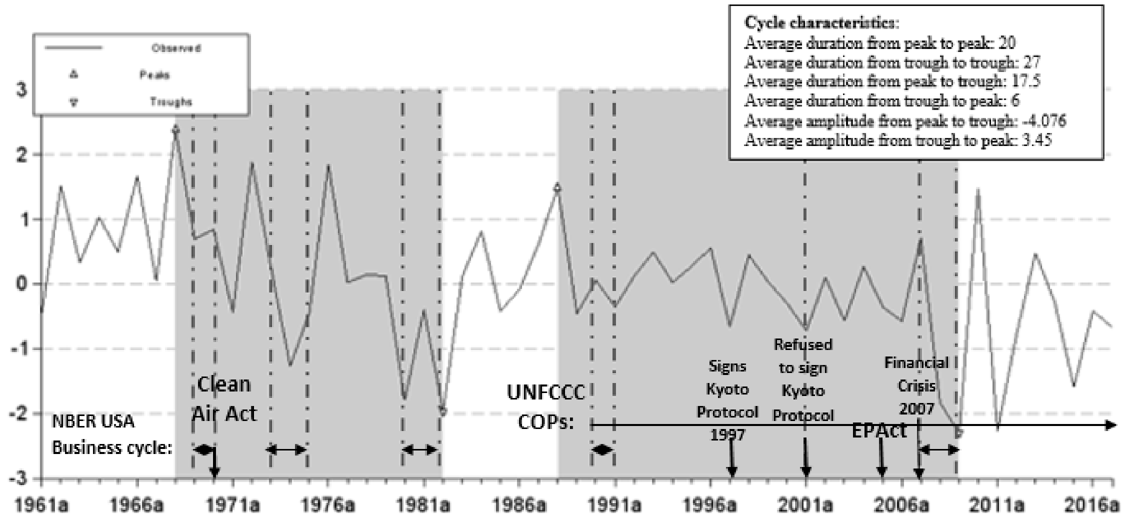

Fig. 2: Dating the USA common cyclical environmental performance

Source: Own compilation using Harding and Pagan [16].
Note: Shaded areas correspond to the declining phases in USA CO_2 emissions fluctuations. Dashed lines marked with horizontal arrows correspond to the business cycle recession phases according to the NBER chronology.

5.2. Results of the dynamics of cyclical convergence.

The time-varying parameter model proposed in the methodological section is employed to investigate how the dynamics of state cyclical convergence has evolved over the period 1970-2017. In the analysis presented in the previous section, it has been found that the synchronization across US states can be considered weak for around half of the states and we detect heterogeneities in the importance of national fluctuations to explain the behavior at the state level. However, we must also take into account in this analysis what the trajectory of the synchronization has been and check if at least it has increased over time. The continuum of results obtained in the estimation of the time-varying parameter model and their t-statistics are shown in Figures 3-6. The 50 US states are separated into 4 groups for reporting purposes in terms of their cyclical evolution.

Figure 3 show the results for the states that are considered the closest to the US fluctuation pattern, since the common factor has a high explanatory capacity and they have maintained the higher correlation values in terms of cyclical convergence (showing correlation greater than 0.65 at the end of the period). They are 13 states which in the 1970s had uneven trajectories, but since the 1980s, they have maintained a favorable evolution regarding their cyclical convergence, with significant increases in the degrees of convergence with the cyclical factor. Nevertheless, a decrease is observed in their cyclical convergence since the US refused to sign the Kyoto protocol in 2001, which increases again after the financial crisis. In this group we can differentiate the states that have reached correlation greater than 0.7, but they are the ones that experienced the greatest drop in their correlation in the 2000s, although they manage to recover at the end of the period (such is the case of Pennsylvania, Ohio, Michigan, Minnesota and Florida). While others, such as Tennessee and North Carolina, remain with high and stable correlations (around 0.65) throughout the years studied. Finally, states like Virginia and Georgina, despite maintaining correlations less than 0.65 during most of the period, experienced an increased in their cyclical correlation until reaching values higher than 0.65 after the financial crisis.

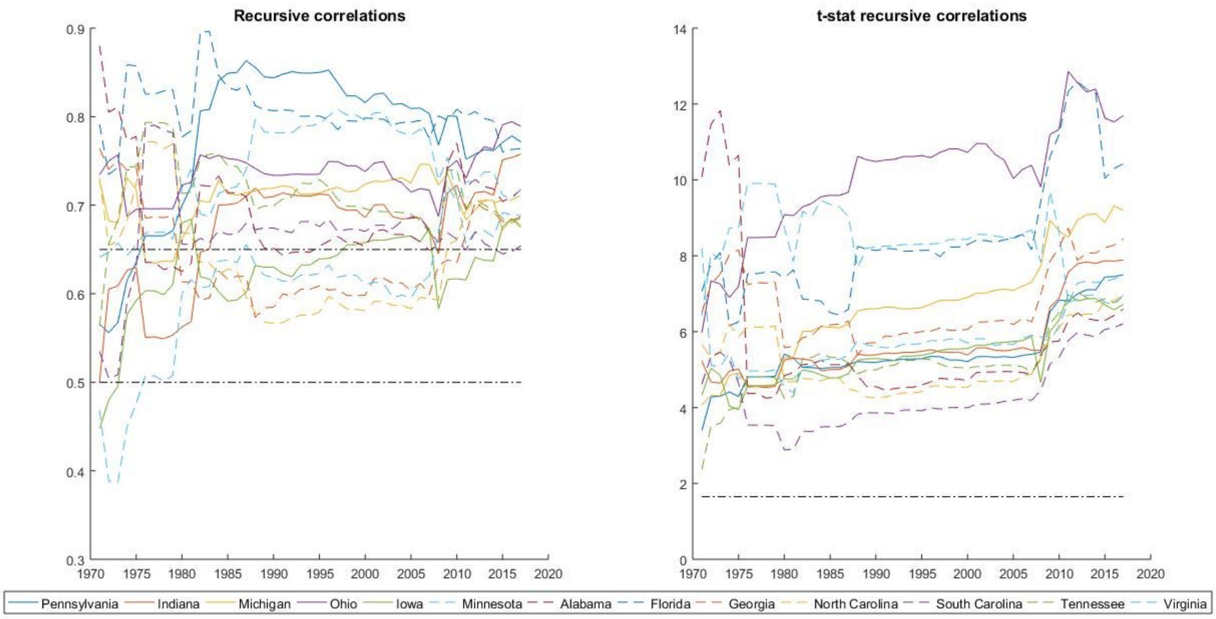

Fig. 3: Cyclical convergence of USA States – Group 1. States with $\beta_j(\tau)$ ≥0.65

Note: Initial trimming to estimation of model (2) is at 20% and the bands of t-stat is at 5% significance.

Figure 4 shows the results for the second group that also includes states with high correlation (between 0.5-0.65) over the period and show similar trajectories of their cyclical correlation to the group 1, but, unlike them, fail to recover and achieve an increase in their cyclical convergence at the end of the period. This group includes the states such as those of Nebraska, California and Texas, which until the financial crisis maintain a correlation greater than 0.65, but the financial crisis negatively affect the path of cyclical convergence that they had experienced and reduce their correlation below

0.65. In this group we can find states such as those of New York, Illinois, Wisconsin and Kansas, which have maintained a stable cyclical convergence that ranges from 0.5 to 0.65 since the 80s and during most of the years studied.

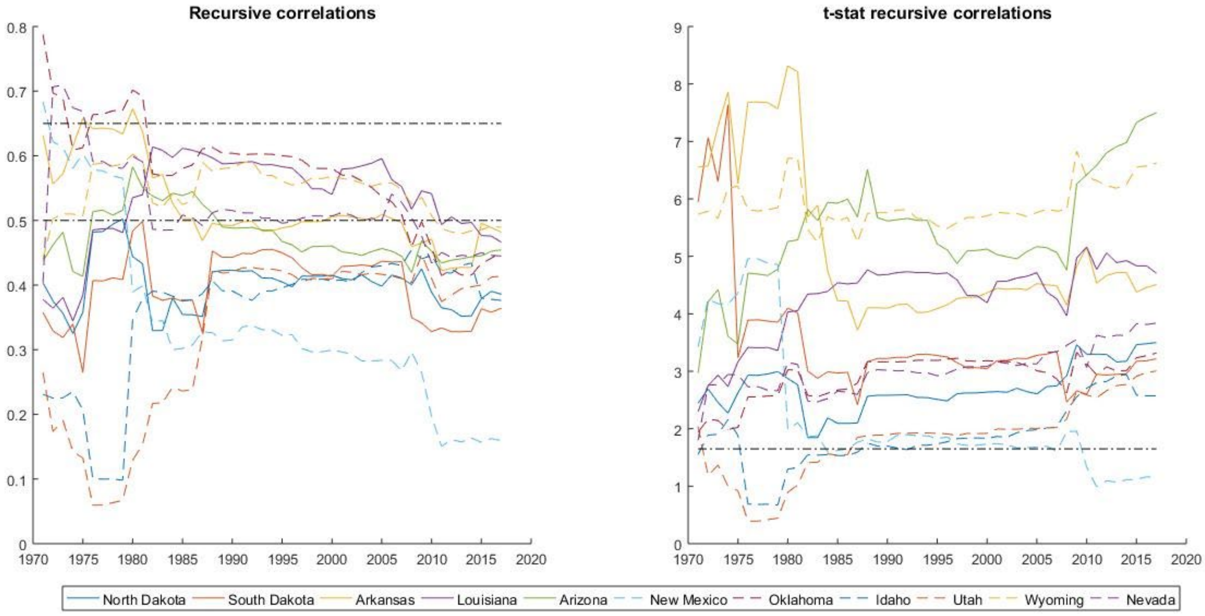

Fig. 4: Cyclical convergence of USA States –Group 2. States with $\beta_j(\tau)$ ≥0.5

Note: Initial trimming to estimation of model (2) is at 20% and the bands of t-stat is at 5% significance.

Results of the third group are shown in Figure 5. This group includes states experiencing a reduction in their convergence pattern almost during the whole period, and specially with the financial crisis. In this group, there are states like Louisiana and Nevada that had a strong correlation with the national fluctuation pattern until the 2000s, but since then they have undergone a reduction of their cyclical convergence which, at the end of the period studied, results in their correlation being below 0.5. There are also states like North Dakota and South Dakota that maintain a weak cyclical correlation throughout most of the period, and which also show an unfavorable trajectory as to their cyclical convergence after the financial crisis.

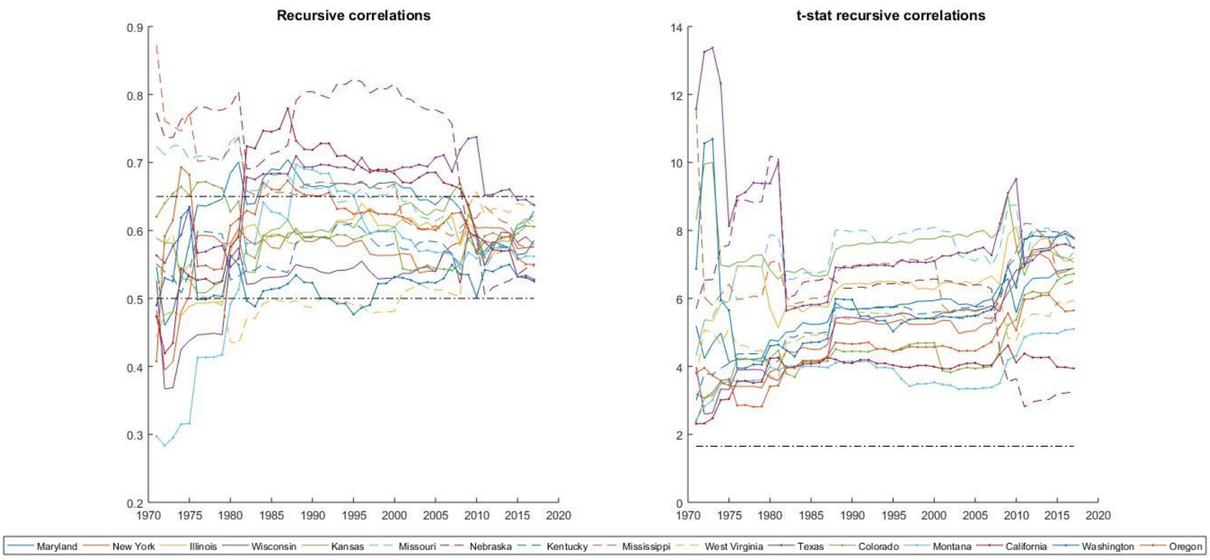

Fig. 5: Cyclical convergence of USA States- Group 3. States with $\beta_j(\tau) < 0.5$

Note: Using the test proposed in Cendejas et al., [15], we have detected a structural break in New Mexico in 1977.

Finally, Figure 6 comprises the rest of the states. In this group we find states that have shown not synchronization in the analysis accomplished in the previous section and with the results obtained about the dynamics of their cyclical convergence we confirm that they follow independent patterns. These are the states of Alaska, Rodhe Island and Vermont. We also find in this group small states from the East coast and Hawaii. For these states, results indicate a reduction of their cyclical convergence over the period. States such as Massachusetts show an increase in cyclical convergence in the 2000s, but nevertheless, its correlation remains below 0.5. In the case of the state of Delaware, this state maintains a stable cyclical convergence with a correlation close to 0.5, with a significant increase in convergence in the mid-2000s, but this trajectory is reversed with the financial crisis.

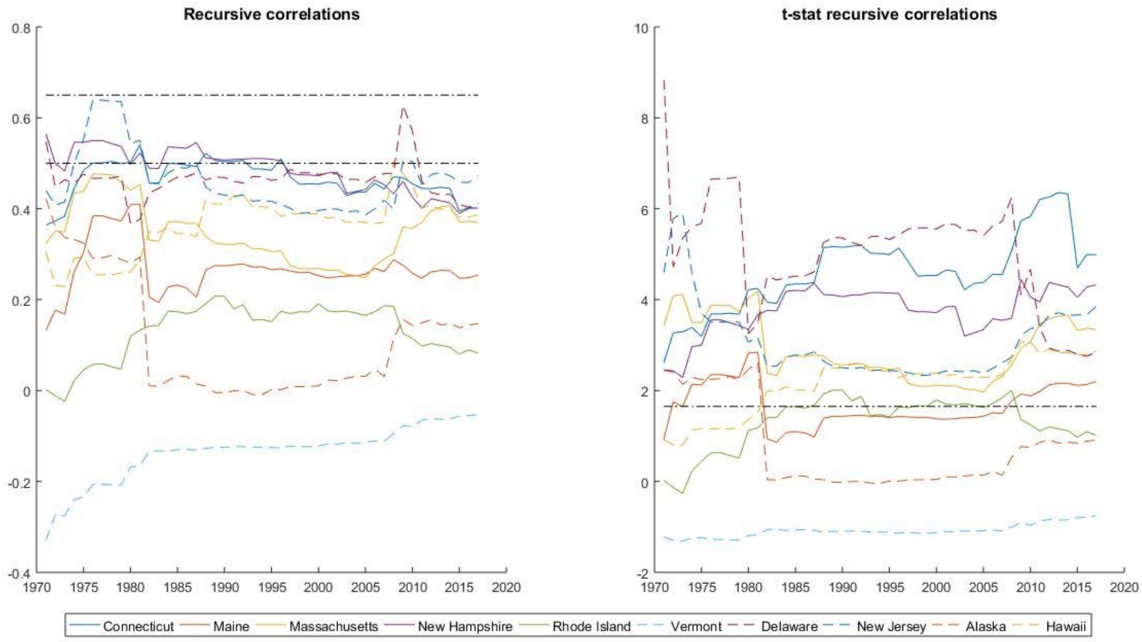

Fig. 6: Cyclical convergence of USA States – Group 4. Rest of the states
Note: Initial trimming to estimation of model (2) is at 20% and the bands of t-stat is at 5% significance.

In order to more intuitively follow the dynamics of the cyclical convergence in the US states, maps of state-level correlation for 1970, 1995 and 2017 are provided in Figures 7-9. The first one depicts cyclical convergence correlations at the starting point of our data set for the analysis of recursive correlation across the US states, 1970, and the second and third ones show this information for 1995 and for the last year we use, 2017. For this last year, we add the information about the states that signed the US Climate Alliance. The darker the shading of map areas, the higher the cyclical convergence correlation. It is straightforward to perceive that the states on the East Coast are the ones that have maintained correlations above 0.65 throughout the period. On the East Coast we also find most of the member states of the US Climate Alliance, many of which are small states. In the case of states pertaining to the West Coast, we find that California, Oregon and Washington increase their cyclical correlation during the first period, but in the following decades they experience a decrease in their correlation. They are also signatory states of the US Climate Alliance. For the rest of states, more heterogeneous trajectories are observed, which generally show stagnation in their cyclical convergence dynamics since the 2000s.

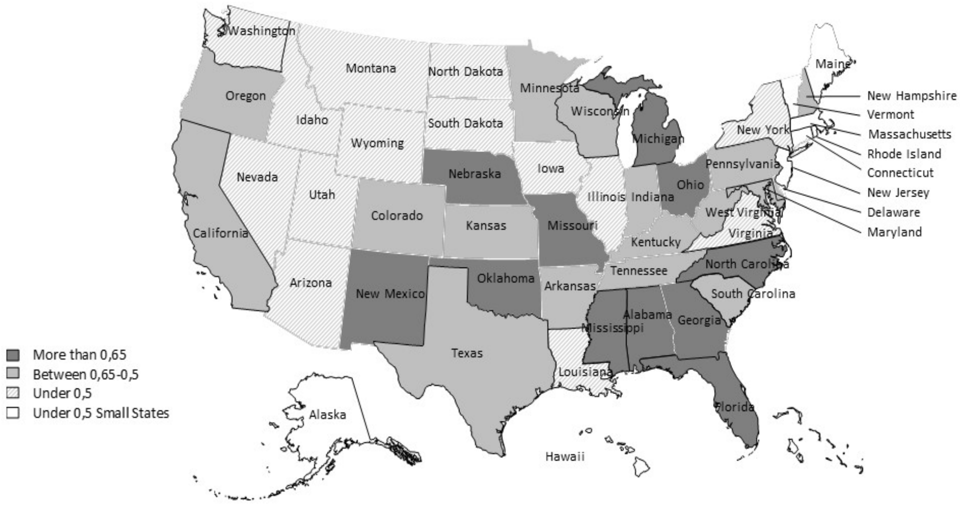

Fig. 7. State level correlation for 1970[22]

Fig. 8. State level correlation for 1995

[22] Figs. 7, 8 and 9 we made with a Map of USA by States was edited by www.showeet.com.

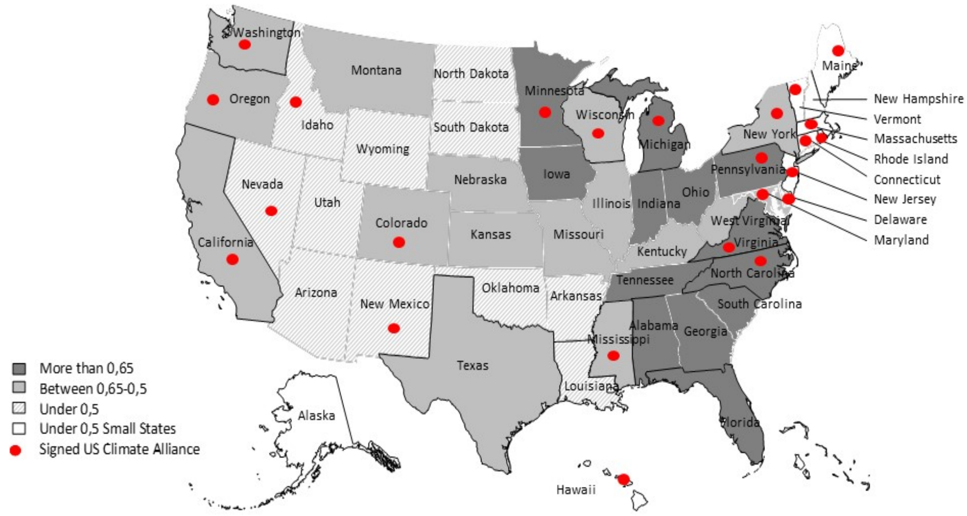

Fig. 9.- State level correlation for 2017 and State signatories US Climate Alliance

5.3. Results and discussion.

In this paper, we based our analysis on a database which is compiled from information at the state level between 1960 and 2017. This evidence is the first for the application of DFM to investigate cross-state links, in the form of co-fluctuations patterns of per capita carbon dioxide emissions across the US states. This unobserved component model allowed us to measure the degree of synchronization and the capacity of the factor to explain state fluctuations. We ranked the states according to the level of cross-state links in the fluctuations of CO_2 emissions and the trajectories of their cyclical convergence. We observed that 47 out of the 50 US states show significant factor loadings and the analysis of their recursive correlations favor the existence of cyclical convergence over the years studied. However, while we provide support for short-run synchronization, the results for 28 states are below 0.5, which can be considered to mean that they are weakly synchronized. Following these results, establishing national policies to control climate change for these states would have less impact on the cyclical behavior of its fluctuations and then on mitigation CO2 emissions.

In the analysis of the cyclical properties of the US fluctuations we also observed that changes in emissions are more symmetrical in amplitude than duration, which convinces us of the difficulties for national environmental initiatives to achieve a sustained impact on emissions. We also find that the financial crisis gives rise to a new phase of increasing in the rate of growth of the emissions from 2009, which indicates that business cycles are related to the consequences of the global financial crisis of 2007-08 and do not significantly affect the level of CO2 emissions. These findings are in line with the results of (Shahiduzzaman & Layton [8], Khan et al., [9] and Gozgor el al., [10]).

We also found strong evidence in favor of increasing differences in the level and trajectories of the states using a time-varying parameter model. According to their level of cyclical correlation (above or below 0.5), but there are also significant differences in the evolution across the states. The refusal of the US to sign the Kyoto protocol and the financial crisis are events that have dissimilar effects in their trajectories. After the financial crisis only 13 states show statistically significant increases in the degrees of convergence, while the rest of states show more unfavorable trajectories and their cyclical correlation are reduced. This result is in line with recent literature that show that most of the US states do not converge (Li et al., [22]). Therefore, policymaker should not support the implementation of national mitigation policies unless the states intensify their cross-state links. There might not be much scope for further cyclical convergence in the future, thus rendering it more difficult for national policies to fight climate change.

Our results also reveals the stationarity of the factor which implies that the effects of national environmental initiatives on the emissions states could only have transitory effects. According to it, differences in cyclical behavior across states would persist, which implies that policymakers should be concerned with the design of mitigation strategies that allow for differences in emission cycles. These findings have contributed to understanding that the difficulties in increasing the synchronization of the US CO_2 emissions highlight the importance of the states to lead the climate change mitigation actions. State initiatives such as the Climate Leadership across the Alliance are committed to implementing policies to reduce carbon pollution and promote clean energy deployment that advance the goals of the Paris Agreement, aimed to reduce GHE by at least 26-28 percent below 2005 levels by 2025.

6. Conclusions

In this paper, we investigated the relevance of synchronization as an important factor in the design of mitigation CO2 policies. This empirical study extends the literature on convergence of carbon dioxide emissions, in serving as the first paper to test cyclical convergence to investigate short run characteristics of CO_2 emissions across the US states. Understanding cyclical convergence helps in assessing whether national climate change policies can be effective and should thus be reinforced. To this end, we use of a dynamic unobserved component approach and a time-varying parameter model which makes possible to estimate the short run dynamics of energy convergence across US states over the extended period 1960-2017. This type of analysis has not received enough attention in the literature so far. The empirical findings reveal the existence of cross-state links in the fluctuations of CO_2 emissions, although the degree to which a good part of the states are co-moving is weak. We also find that cyclical convergence patterns differ considerably in both the level and trajectories across the US states. The difficulties in increasing synchronization of the US CO_2 emissions and the transitory effects of national policies highlight the importance of the states to lead climate change mitigation actions.

Overall, our paper demonstrates that further studies should consider the synchronization of the emission cycles in their energy analysis to increase understanding of the short-run properties and shape the effective energy policy to reduce CO_2 emissions. Future papers on the subject can focus on the comparison of the emissions fluctuations patterns of the US with the rest of signatory countries of the Kyoto protocol. This could be done with a methodology similar to the one applied in this paper. Such a study would potentially provide insight on the likelihood of reaching the proposed global targets.

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.

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This article was written during the COVID-19 lockdown period. We dedicate it to all the people who, in the discharge of their duties, allowed us to be protected at home.

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Annex

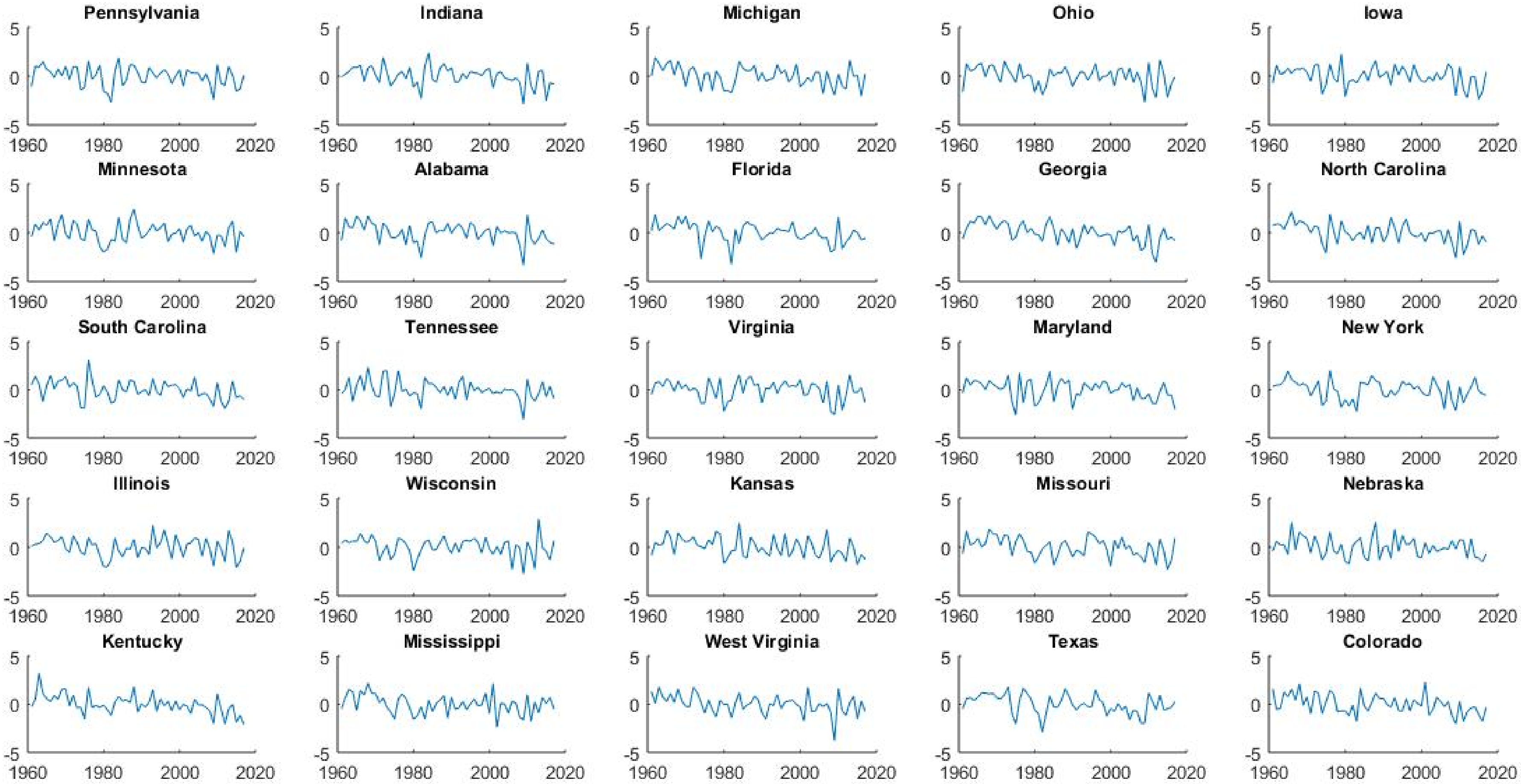

Fig. A1: The cycle of CO_2 emissions in USA by States

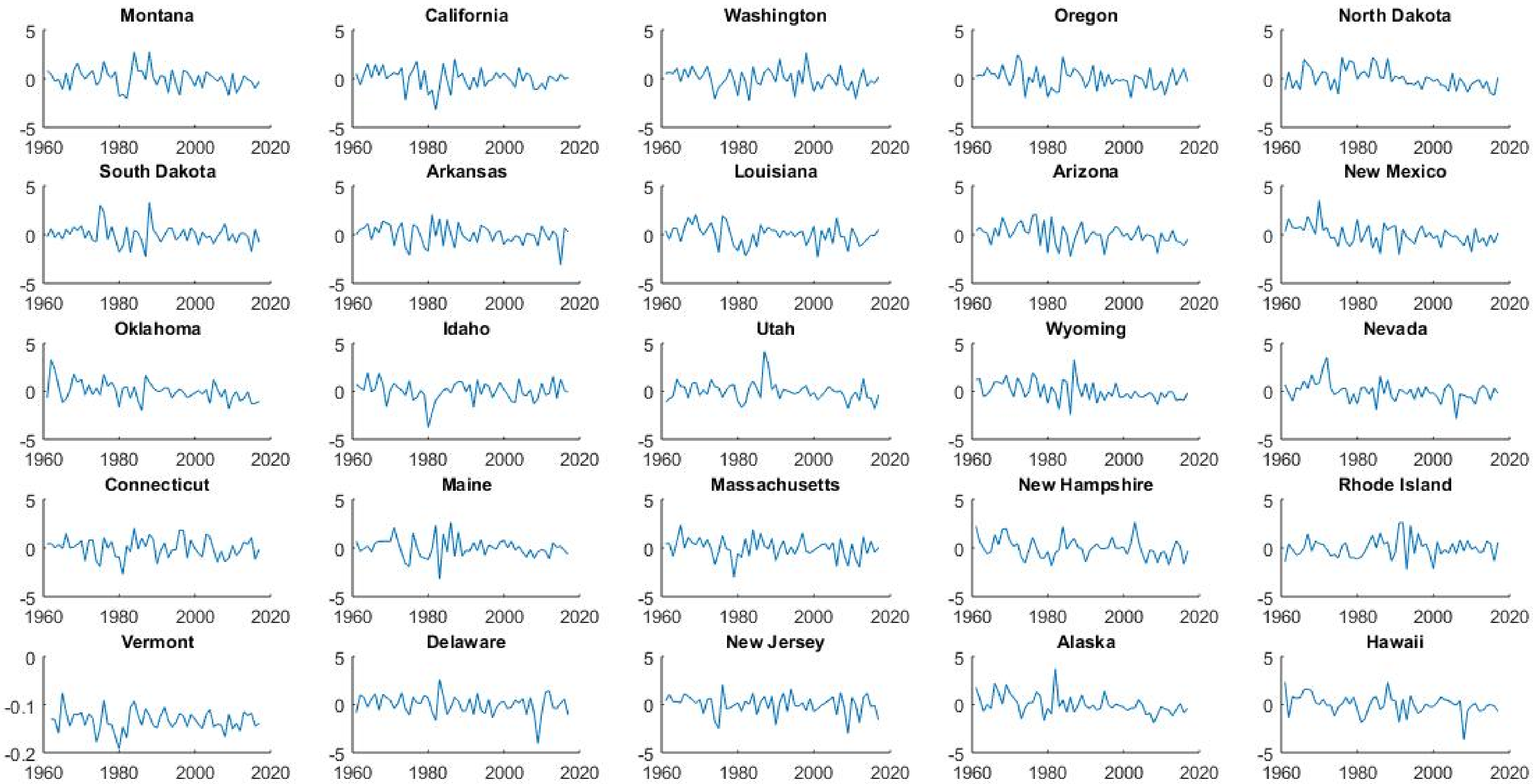

Fig. A1: The cycle of CO_2 emissions in USA by States (continued)