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Convergence of GHGs emissions in the long-run: aerosol precursors, reactive gases and aerosols—a nonlinear panel approach

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Abstract
Anthropogenic emissions of reactive gases, aerosols and aerosol precursor compounds are responsible for the ozone hole, global warming and climate change, which have altered ecosystems and worsened human health. Environmental authorities worldwide have responded to these climate challenges through the 2030 Agenda for Sustainable Development. In this context, it is key to ascertain empirically whether emission levels are converging among the countries forming the industrialized world. In doing so, we focus on 23 industrialized countries using a novel dataset with ten series of annual estimates of anthropogenic emissions that include aerosols, aerosol precursor and reactive compounds, and carbon dioxide over the 1820–2018 period. We apply four state-of-the-art panel unit root tests that allow for several forms of time-dependent and state-dependent nonlinearity. Our evidence supports stochastic convergence following a linear process for carbon dioxide, whereas the adjustment is nonlinear for black carbon, carbon monoxide, methane, non-methane volatile organic compounds, nitrous oxide, nitrogen oxides and sulfur dioxide. In contrast, ammonia and organic carbon emissions appear to diverge. As for deterministic convergence, carbon dioxide converges linearly, while black carbon, carbon monoxide, nitrogen oxides, non-methane volatile organic compounds and sulfur dioxide adjust nonlinearly. Our results carry important policy implications concerning the achievement of SDG13 of the global 2030 Agenda for Sustainable Development, which appears to be feasible for the converging compounds.

Keywords GHGs emissions convergence · Nonlinearities · State-dependence · Structural breaks · 2030 Agenda for Sustainable Development

JEL Classification C24 · C33 · Q50 · Q53 · Q54 · Q58

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1 Introduction

The aim of the European Green Deal is to decarbonize the European Union's energy system from a fuel-based energy system to a decarbonized economy (European Commission, 2018, 2019). This will be achieved by reducing net greenhouse gas (GHG) emissions by 55% below 1990 levels by 2030, from the 20% reduction achieved by 2020. In addition, net-zero GHG emissions in 2050 are to be achieved. This will be done by creating natural carbon sinks (e.g., forests) and carbon capture and storage technologies, which will make the European Union (EU) the first climate-neutral area in the world. EU Authorities' policy efforts can be framed within a broader 2030 Agenda for Sustainable Development endorsed globally by the United Nations Environment Programme (UNEP). The 2030 Agenda consists of 17 goals, of which sustainable development goal 13 (SDG13) is key for the achievement of the full 2030 Agenda and the Paris Agreement on climate change. SDG13 consists of taking urgent action to combat climate change and its impacts through providing enough financial flows, improved technology and enhanced human and institutional capacity building, thereby increasing public awareness. Along similar lines, the adoption of the Paris Agreement in 2015 pursues to globally combat climate change by keeping a global temperature rise this century well below two degrees Celsius above pre-industrial levels.

According to Hoesly et al. (2018), "anthropogenic emissions of reactive gases, aerosols, and aerosol precursor compounds have substantially changed atmospheric composition and associated fluxes from land and ocean surfaces." This has brought atmospheric chemical reactions that are responsible for several climate phenomena such as the ozone hole, global warming and climate change, or the cooling effect caused by the sunlight reflection in highly polluted clouds. These climate changes have 1) produced alterations in the radiative balances of the atmosphere (Zhao et al., 2019), 2) affected human health in the form of higher mortality and morbidity and 3) altered terrestrial and aquatic ecosystems.

Considering the global scope of the above environmental policy agenda to tackle these climate challenges, it is key to ascertain empirically whether emission levels are converging among the countries forming the industrialized world. If the evidence points to the existence of emissions convergence among industrialized countries, this would indicate that SDG13 of the 2030 Agenda and the postulates and targets of the Paris Agreement are more feasible to be achieved than otherwise. In addition, a per capita emissions allocation scheme would make more sense if there is evidence of convergence, without the need for substantial resource transfers through international emissions trading or cross-border movements of industries with high-pollution intensity. Also, harmonization in the field of abating anthropogenic emissions may be difficult to implement in the absence of emissions convergence, which would hinder the management and control of pollutants emissions. Hence, emissions convergence in the developed world would encourage large emitters like China and India to take steps to cut their emissions. Furthermore, most projection models guiding policymakers in their formulation of emission abatement strategies to combat climate change assume convergence in emissions.

Given the far-reaching policy implications of attaining emissions convergence in the industrialized world, we investigate the existence of stochastic and deterministic convergence among a panel of 23 Organization for Economic Co-operation and Development (OECD) countries for ten series of annual estimates of anthropogenic emissions that include carbonaceous aerosols (black carbon –BC–, organic carbon –OC–), aerosol precursor and reactive compounds (methane –CH_4–, carbon monoxide –CO–, nitrous oxide

–N_2O–, nitrogen oxides –NO_x–, ammonia –NH_3–, non-methane volatile organic compounds –NMVOC–, sulfur dioxide –SO_2–), and carbon dioxide –CO_2– over the period 1820–2018. This is a step forward since it has implications in the policies to tackle climate change. It may help overcome the fact that so far countries have solely focused on curbing CO_2 emissions and ignored other pollutants.[1]

In the empirical exercise, we apply four state-of-the-art panel unit root tests that allow for several forms of time-dependent and state-dependent nonlinearity.[2] More specifically, these are the panel unit root tests of Ucar and Omay (2009)—UO hereafter, Emirmahmutoğlu and Omay (2014)—EO hereafter, Omay et al., (2018a, 2018b)—OHS hereafter and Omay et al. (2021b)—OSS hereafter. First, UO and EO are state-dependent nonlinear panel unit root tests, which are based on symmetric exponential smooth transition autoregressive (ESTAR) model and asymmetric exponential smooth transition autoregressive (AESTAR) model, respectively.[3] Second, OHS and OSS panel unit root tests exhibit time-varying nonlinearity in deterministic components: a permanent break modeled by a logistic smooth transition (LSTR) function and multiple smooth breaks modeled by the flexible Fourier function, respectively.[4]

Our study contributes to the emissions convergence literature in several respects. First, it employs the above four nonlinear panel unit root tests which, in addition to allowing for a wide variety of nonlinear dynamics, they control for cross-country heterogeneity and cross-dependencies via Sieve bootstrap methods. As shown below, no previous study on emissions convergence deals with this issue with such a large battery of nonlinear panel unit root tests. In addition, most of these nonlinear panel tests have not been used in this literature before. Second, no previous study has analyzed convergence dynamics for such a large number of pollutants. More specifically, we focus on two series of aerosols, seven series of aerosol precursor compounds and reactive gases, and CO_2 which constitutes the main GHG for a very lengthy period of two centuries (1820–2018). They stem from a novel database which, to the best of our knowledge, has not been used in this literature. Third, we investigate two notions of time-series convergence: one weaker given by stochastic convergence and one stronger given by deterministic convergence.

Our findings support stochastic convergence following: linear adjustment for CO_2, symmetric ESTAR adjustment for BC, CO, NO_x and SO_2 emissions, AESTAR adjustment for NMVOC emissions, logistic adjustment capturing a permanent structural break in CH_4, and both state and time dependent nonlinearity in N_2O. On the contrary, the evidence points to divergence for NH_3 and OC emissions. As for deterministic convergence, CO_2 emissions converge linearly, NO_x follows symmetric ESTAR adjustment, BC, CO, NMVOC and SO_2 adjust following AESTAR dynamics, while CH_4, N_2O, NH_3 and OC fail to converge deterministically.

The remainder of the paper is structured as follows. Section 2 provides a literature review on the topic. Section 3 presents the data, the empirical strategy and a brief

[1] Stern (2014) in fact provides evidence that CO_2 emissions have declined in developed countries, while the level of other pollutants remain still high.

[2] State-dependent (regime-wise) nonlinearity implies nonlinearity in the speed of mean reversion and time-dependent (structural breaks) nonlinearity implies nonlinearity in the deterministic components.

[3] They are built on the basis of the univariate Kapetanios et al. (2003) –KSS hereafter– and Sollis (2009) tests, respectively.

[4] They are built on the basis of the univariate Leybourne et al. (1998) –LNV hereafter– and Enders and Lee (2012) –EL hereafter– tests, respectively.

description of the nonlinear panel unit root tests used in the empirical analysis, leaving the econometric details to the unpublished appendix. Section 4 reports the results, and Sect. 5 provides some policy implications and concludes.

2 Literature review

Before presenting the literature review, we point out that there are several reasons supporting the presence of nonlinearities in the process of emissions convergence. Firstly, the nonlinear impact of oil price shocks on economic activity is reflected in nonlinear dynamics in pollutants emissions (Hasanov and Telatar, 2011, and references therein). Secondly, the presence of asymmetries in the duration of cyclical phases of CO_2 emissions is closely associated with energy demand patterns, economic activity nonlinear shocks and asymmetries in the duration of phases of the business cycle (Zerbo and Darné, 2019, and Awaworyi-Churchill et al., 2020).[5] Thirdly, the transition across economic regimes takes place gradually because of the expected delay between the occurrence of the shock and the subsequent response of economic agents. Hence, since a great bulk of emissions stems from economic activity, nonlinearities in the latter will be transmitted to the former (Presno et al., 2018). In addition, at the technical level, univariate and panel unit root statistics that fail to incorporate sharp structural change, and threshold and smooth nonlinearities lead to a lack of statistical power (Kapetanios et al., 2003; Perron, 1989), thus biasing the results toward the non-convergence hypothesis.

Due to space considerations, in the literature review, we confine ourselves to the studies analyzing emissions convergence dynamics among industrialized countries, which is the focus of our study. Most of existing studies focus on CO_2, as compared to our wider analysis of ten compounds. The review is presented in a table-format, containing the results of analyses of β-convergence à la Barro and Sala-i-Martin (1992), distribution dynamics following Quah (1996), club-convergence clustering of Phillips and Sul (2007, PS hereafter) and stochastic convergence following Carlino and Mills (1993).[6] Table 1 reviews a total of 55 studies assessing emissions convergence among industrialized countries. This also includes a small number of studies investigating emissions convergence within an industrialized country using data disaggregated at the sectoral and/or state/regional level.

As shown in Nguyen Van (2005), Aldy (2006), Herrerías (2012), Jobert et al. (2010), Strazicich et al. (2003), Duro and Padilla (2013) and Karakaya et al. (2019b), distribution dynamics and conditional β-convergence analyses mostly favor CO_2 emissions convergence among industrialized countries. In contrast, Kounetas (2018) finds no evidence of convergence. Concerning studies using disaggregate data, Apergis et al. (2017), Oliveira and Bourscheidt (2017) and Marrero et al. (2021) favor β-convergence (either absolute or conditional depending on the case), while Aldy (2007) fails to find CO_2 emissions convergence among U.S. states using distributional analysis.

[5] Their evidence points to the fact that contractionary phases of CO_2 emissions are relatively lengthier than expansionary ones. Cai et al. (2018) also find evidence of asymmetric behavior of per capita emissions in 21 OECD countries, which is detected at selected quantiles.

[6] See Pettersson et al. (2014) and Payne (2020) for reviews of the literature on CO_2 emission convergence, which include also articles analyzing global samples, developing and emerging economies samples, and within-country subnational studies.

Table 1 Literature review

Article	Data used	Testing approach	Main findings
A. Distribution Dynamics analysis of Quah (1996)			
Nguyen Van (2005)	1966–1996, per capita CO_2, 26 industrial countries	Nonparametric analysis of distributional dynamics estimated with kernels	Evidence of convergence
Herrerías (2012)	1920–2007, per capita CO_2, 25 EU countries	Nonparametric analysis of distributional dynamics based on kernels, unweighted and weighted by population and economic size	Unweighted analysis renders more convergence after the 1970s. Weighted analysis renders evidence of much faster convergence
Kounetas (2018)	1970–2010, CO_2 emissions intensity (CO_2 emissions over GDP), 23 EU countries	Nonparametric analysis of distributional dynamics based on kernels	No evidence of convergence
Aldy (2006)	1960–2000, per capita CO_2, 23 OECD countries	Nonparametric analysis of distributional dynamics based on kernels. Stochastic convergence based on univariate generalized least squares augmented Dickey and Fuller (1979)—ADF—tests	Evidence of convergence in the emissions distribution, but mixed evidence regarding stochastic convergence
Aldy (2007)	1960–1999, consumption and production per capita CO_2, 50 US states	Distributional analysis via Markov chain transition matrix methods, and stochastic convergence via the panel unit root test of Im et al. (2003)—IPS hereafter	Clear evidence of divergence in production CO_2 per capita and lack of convergence for consumption CO_2 per capita
Duro and Padilla (2013)	1990–2007, per capita CO_2, 27 EU countries	Indices of Polarization	Evidence of a clear fall in polarization since the mid-1990s
B. β- and σ-convergence (Barro and Sala-i-Martín, 1992)			
Jobert et al. (2010)	1971–2006, per capita CO_2, 22 EU countries	β-convergence using Bayesian shrinkage estimation	Evidence of both absolute and conditional β-convergence with the industry share playing a key role
Strazicich and List (2003)	1960–1997, per capita CO_2, 21 OECD countries	Conditional β-convergence and stochastic convergence with IPS panel unit root test	Evidence of conditional β-convergence (with gasoline and average winter temperature as controls) and stochastic convergence

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Karakaya el al. (2019b)	1990–2015, production-based and consumption-based CO_2 emissions, 35 Annex B countries (mainly industrialized)	Absolute and conditional β-convergence using regression analysis	Evidence of absolute and conditional β-convergence for production-based CO_2 emissions. Lack of absolute β-convergence for consumption-based CO_2 emissions, but evidence of conditional β-convergence once controls are added
Apergis et al. (2017)	1997–2013, CO_2 emissions intensity, 50 U.S. states	Absolute β-convergence, σ-convergence and stochastic convergence through several panel unit root tests	Evidence favors absolute β-convergence and σ-convergence, but not stochastic convergence
Oliveira and Bourscheidt (2017)	1995–2007, per capita CO_2, CH_4 and CO emissions, 40 countries (27 EU countries, and the 13 largest economies around the world)	Conditional β-convergence using random and fixed effects, and Generalized Methods of Moments (GMM) dynamic panel estimation	Evidence of conditional β-convergence in per capita CH_4 emissions in agriculture, food, and services sectors. Moderate evidence of conditional β-convergence in per capita CO_2 emissions in agriculture, food, non-durable goods manufacturing, and services
Fernández-Amador et al. (2019)	1997–2014, per capita CO_2, 66 countries and 12 composite regions	Conditional β-convergence using a Bayesian robust structural model	No evidence for specific convergence dynamics in the EU, OECD, or the countries subject to binding emissions constraints in the Kyoto Protocol
Marrero et al. (2021)	1990–2014, per capita road transport CO_2 emissions, 22 European countries	Conditional β-convergence using pooled ordinary least squares, fixed effects, and GMM methods	Evidence of conditional β-convergence with economic activity and fuel prices being particularly influential
*C. Club-convergence (*Phillips & Sul, 2007*)*			
Camarero et al. (2013a)	1960–2008, CO_2 emission intensity, 23 OECD countries	Club-convergence algorithm of PS	Evidence of four convergence clubs and a non-convergent group. Convergence dynamics are mainly driven by the dynamics of the carbonization index
Camarero et al. (2013b)	1980–2008, eco-efficiency indicators for CO_2, NO_x and SO_2, 22 OECD countries	Club-convergence algorithm of PS	Evidence of efficiency improvements mainly in CO_2, with four convergence clubs

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Ulucak and Apergis (2018)	1961–2013, per capita ecological footprint, 20 EU countries	Club-convergence algorithm of PS	Evidence of three convergence clubs
Apergis and Payne (2017)	1980–2013, per capita CO_2, 50 U.S. states (aggregate and by sector and fossil fuel source)	Club-convergence algorithm of PS	Multiple convergence clubs for the aggregate, sectors and two of the three fossil fuel sources (natural gas and coal), while full club convergence for oil
Emir et al. (2019)	1990–2016, carbon intensity, EU28 countries	Club-convergence algorithm of PS	Evidence of five to seven convergence clubs
Morales-Lage et al. (2019)	1971–2012, sectoral per capita CO_2, 28 EU countries	Club-convergence algorithm of PS	Evidence of multiple convergence clubs, with the core countries (France, Holland, Germany and the UK) being part of the best performing clubs, with some Central and Eastern European countries exhibiting divergence
Apergis and Garzón (2020)	1990–2017, greenhouse gas emissions per capita, 19 Spanish regions	Club-convergence algorithm of PS	Evidence of four convergence clubs
Cialani and Mortazavi (2021)	1970–2018, per capita CO_2, 28 EU countries (aggregate and two key sectors: industry and manufacturing)	Club-convergence algorithm of PS	At most five convergence clubs in the aggregate, industry and manufacturing sectors
D. Stochastic convergence			
Nourry (2009)	1950–2003, per capita CO_2 and SO_2, 29 OECD countries	Pairwise approach to stochastic convergence following Pesaran (2007)	Lack of evidence of stochastic convergence
El-Montasser et al. (2015)	1990–2011, CO_2, CH_4, N_2O, petrofluorocarbons (PFCs), hydrofluorocarbons (HFCs) and sulfur hexafluoride (SF_6), G7 countries	Pairwise approach to stochastic convergence following Pesaran (2007) and stochastic convergence using the panel stationarity test with multiple breaks of Carrion-i-Silvestre et al. (2005) –CBL hereafter	No evidence of convergence, with only a small decline in GHGs emissions across countries recently
Westerlund and Basher (2008)	1870–2002, per capita CO_2, 16 OECD countries	Stochastic convergence via three panel unit root tests with a common factor representation	Strong evidence of convergence with an unbiased half-life estimate of six years

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Romero-Avila (2008)	1960–2002, per capita CO_2, 23 OECD countries	Stochastic convergence with the panel stationarity test with multiple breaks of CBL	Strong evidence of both stochastic and deterministic convergence
Yavuz and Yilanci (2013)	1960–2005, per capita CO_2, G7 countries	Stochastic convergence based on a threshold autoregressive panel unit root test	Data are split into two regimes, with convergence in the first regime, while divergence in the second partly caused by the oil shocks of the 1970s
Camarero et al. (2008)	1971–2002, two environmental performance indicators: based on the production process and on CO_2 emissions relative to GDP, 22 OECD countries	Stochastic convergence based on a panel unit root test of seemingly unrelated regression (SUR)-ADF type	Evidence of convergence for all countries with the first indicator and for 15 with the second
Camarero et al. (2011)	1950–2006, per capita CO_2, 22 OECD countries	Stochastic convergence using the univariate nonlinear unit root test of KSS	No evidence of convergence
Barassi et al. (2008)	1950–2002, per capita CO_2, 21 OECD countries	Stochastic convergence with a battery of univariate and panel stationarity and unit root tests	No evidence of convergence
Barassi et al. (2011)	1870–2004, per capita CO_2, 18 OECD countries	Stochastic convergence with local Whittle estimator and fractional integration tests	Evidence of fractional integration supportive of slow convergence in 13 out of 18 OECD countries
Barassi et al. (2018)	1950–2013, per capita CO_2, 28 OECD countries	Stochastic convergence using fractional integration tests with structural breaks	Evidence of convergence in only 30 to 40% of the countries
Chang and Lee (2008)	1960–2000, per capita CO_2, 21 OECD countries	Stochastic convergence using univariate Lagrange Multiplier (LM) unit root tests allowing for two structural breaks	Evidence of stochastic convergence
Lee and Chang (2008)	1960–2000, per capita CO_2, 21 OECD countries	Stochastic convergence with SUR-ADF tests	Evidence of convergence in only seven countries
Lee et al. (2008)	1960–2000, per capita CO_2, 21 OECD countries	Stochastic convergence based on univariate unit root tests with structural breaks	Evidence of convergence in 13 countries

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Lee and Chang (2009)	1950–2002, per capita CO_2, 21 OECD countries	Stochastic convergence with panel unit root tests and the panel stationarity test with multiple breaks of CBL	Evidence of convergence
Ozcan and Gultekin (2016)	1960–2013, per capita CO_2, 28 OECD countries	Stochastic convergence using two-break LM and residual-augmented least-squares-regression (RALS)-LM unit root tests with breaks	Evidence of convergence in most countries when structural breaks are incorporated
Li et al. (2014)	1990–2010, per capita CO_2, 50 U.S. states	Stochastic convergence using sequential panel selection methods applied to the panel KSS test with a Fourier extension	Convergence in only 12 of the 50 US states
Payne et al. (2014)	1900–1998, per capita SO_2, 50 U.S. states	Stochastic convergence using RALS-LM unit root tests with structural breaks	Evidence of stochastic convergence
Presno et al. (2018)	1901–2009, per capita CO_2, 28 OECD countries	Stochastic convergence using univariate stationarity tests allowing for quadratic trends with smooth transitions	Evidence of stochastic convergence for the countries under study, but coupled with some dispersion particularly among developed countries
Erdogan and Acaravci (2019)	1960–2014, per capita CO_2, 28 OECD countries	Stochastic convergence using the panel stationarity with multiple breaks of CBL and an extended version with a Fourier function	Evidence of convergence with the CBL test, but mixed evidence with the Fourier extension (stationarity at the univariate level and nonstationarity at the panel level)
Karakaya et al. (2019a)	1960–2013, per capita CO_2, 16 OECD countries	Stochastic convergence with univariate and panel cross-sectionally augmented ADF tests	No evidence of convergence
Cai and Wu (2019)	1960–2014, per capita CO_2, 21 OECD countries	Stochastic convergence with the panel stationarity test with breaks of CBL and an extension with a Fourier function	Evidence of convergence in 11 countries with the extended version
Solarin (2019)	1961–2013, per capita CO_2, 27 OECD countries	Stochastic convergence using RALS-LM unit root tests	Evidence of convergence in 22 countries

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Sephton (2020)	1950–2014, per capita CO_2, 28 OECD countries	Stochastic convergence using fractional integration tests. Structural change is allowed via Chebyshev polynomials and nonlinearities via the multivariate adaptive regressions splines model	Evidence of convergence in nearly all series once nonlinearity and serial correlation are permitted
Solarin and Tiwari (2020)	1850–2005, per capita SO_2, 32 OECD countries	Stochastic and deterministic convergence using the panel stationarity test with breaks of CBL, and a panel stationarity test with a common factor and a Fourier function	Evidence of both notions of convergence with the CBL test and mixed evidence with the Fourier-based panel test
Awaworyi-Churchill et al. (2018)	1900–2014, per capita CO_2, 30 OECD countries	Stochastic convergence using RALS-LM unit root tests with breaks	Evidence of convergence during the whole period, and more pronounced over the postwar period
Ahmed et al. (2017)	1960–2010, per capita CO_2, 162 countries (divided by income-group)	Stochastic convergence using univariate wavelet-based unit root tests	Evidence of convergence in 38 countries of which 20 are high-income countries (18 belong to the OECD), 13 are middle-income and five are low-income countries
Bilgili and Ulucak (2018)	1961–2014, per capita ecological footprint that encompasses carbon emissions and other dimensions, G20 countries	Stochastic convergence using the panel stationarity test with multiple breaks of CBL and the club convergence algorithm of PS	The evidence favors stochastic and deterministic notions of convergence
Sohail et al. (2022)	1960–2018, per capita CO_2, top 20 highest CO_2 emitting countries (including some OECD countries, the BRICS, Iran and Saudi Arabia)	Stochastic convergence using three univariate nonlinear unit root tests	17 countries exhibit stochastic convergence, while three countries (Australia, France and Italy) diverge
Wang et al. (2020)	1971–2013, carbon intensity (carbon emissions per unit of output), 24 countries	Stochastic convergence using Johansen (1991) cointegration tests and σ-convergence	Convergence exists among high and medium–high income countries, while medium and low-income countries diverge

Table 1 (continued)

Article	Data used	Testing approach	Main findings
Solarin et al. (2022)	1781–2014, per capita CH_4 emissions, 37 OECD countries	Stochastic convergence using ADF and Phillips and Perron (1988) unit root tests and a wavelet unit root test with a Fourier extension	Overwhelming evidence of lack of convergence
Erdogan and Solarin (2021)	1960–2016, per capita CO_2, 151 countries of which 53 are high-income countries	Stochastic convergence using Fourier-based wavelet unit root tests	Stochastic convergence in 35 of the 53 high-income countries analyzed, 27 upper-middle-income countries, 30 lower-middle-income countries and 13 low-income countries
Lin et al. (2018)	1950–2013, per capita CO_2, G18 countries	Stochastic convergence using quantile unit root tests	Evidence of stochastic convergence in only five of the 18 countries
Cai et al. (2018)	1950–2014, per capita CO_2, 21 OECD countries	Stochastic convergence using univariate unit root tests with good size and power, and quantile unit root test with and without Fourier extension	The Fourier-extended test provides evidence of convergence in nine countries, with asymmetric behavior being identified at selected quantiles
Solarin et al. (2021)	1750–2019, per capita NO_x emissions, G7 countries (aggregate and sectors)	Stochastic convergence using panel Fourier threshold unit root test	Full convergence for agriculture, energy production and transport sectors, while partial convergence (only in the second regime) in aggregate, industrial sector, residential-commercial-other, and waste sectors

As regards the empirical studies employing the club-convergence algorithm of PS, the eight studies reviewed provide evidence of several convergence clubs, irrespective of whether the focus is on country samples, or state/regions and sectors within a particular country. This finding is consistent with conditional convergence, whereby groups of countries or subnational units sharing structural characteristics converge to their respective steady states.

Concerning studies investigating stochastic convergence by means of univariate and/or panel unit root tests allowing in some cases for structural breaks or nonlinearities, the evidence appears to mostly favor the existence of stochastic convergence in emissions among rich countries. Still, some of the studies provide mixed evidence or evidence against convergence. As a matter of fact, Strazicich et al. (2003), Westerlund and Basher (2008), Romero-Avila (2008), Camarero et al. (2008), Chang and Lee (2008), Lee and Chang (2009), Ozcan and Gultekin (2016), Presno et al. (2018), Awaworyi-Churchill et al. (2018), Solarin (2019), Bilgili and Ulucak (2018), Sephton (2020) and Sohail et al. (2022) provide strong evidence in favor of stochastic convergence among industrialized countries. In contrast, Barassi et al. (2008), Nourry (2009), Camarero et al. (2011), El-Montasser et al. (2015), Karakaya et al. (2019a) and Solarin et al. (2022) find no empirical support for stochastic convergence among industrialized countries.

Somewhere in between, Aldy (2006), Yavuz and Yilanci (2013), Barassi et al. (2011), Barassi et al. (2018), Lee and Chang (2008), Lee et al. (2008), Erdogan and Acaravci (2019), Cai and Wu (2019), Solarin and Tiwari (2020), Ahmed et al. (2017), Lin et al. (2018), Cai et al. (2018), Wang et al. (2020) and Erdogan and Solarin (2021) provide mixed evidence, since only part of the countries under study exhibit stochastic convergence. Concerning the studies investigating stochastic convergence using disaggregate data, Payne et al. (2014) favor stochastic convergence among the US states, whereas Li et al. (2014) provide mixed evidence of stochastic convergence in the US states. We refer the reader to Table 1 for exact details in data used, testing approach and main findings for each of the 55 studies covered in this literature review.

3 Material and methods

3.1 Data description

This paper employs a novel database for ten series of annual estimates of anthropogenic emissions that enables us to compute per capita emission levels of the following pollutants using long-term population data from the Maddison Project Database (2020): aerosol compounds (BC, OC), aerosol precursor and reactive compounds (CH_4, CO, N_2O, NO_x, NH_3, NMVOC, SO_2) and CO_2. The data span over the period 1820–2018 for seven of the pollutants, with the exception of CO_2 emissions that span over the period 1851–2018 and CH_4 and NO_2 that span between 1970 and 2018. The source of the data is the Community Emissions Data System (CEDS) for Historical Emissions (Hoesly et al., 2018) and the version of the dataset used is CEDS v_2021_04_21 Release Emission Data (version v_2021_02_05) (O'Rourke et al., 2021). The dataset is obtained by the Joint Global Change Research Institute of the University of Maryland in collaboration with Pacific Northwest National

Laboratory.[7] In Table 8 in the Appendix, we provide a comprehensive account of the emission series used, data sources and measurement descriptions.

Apart from CO_2 (carbon dioxide), which is the most important GHG,[8] we also consider two major carbonaceous aerosol compounds such as BC (black carbon) and OC (organic carbon).[9] In addition, we analyze seven series of reactive gases and aerosol precursor compounds such as carbon monoxide (CO), nitrous oxide (N_2O), nitrogen oxides (NO_x), sulfur dioxide (SO_2), ammonia (NH_3), methane (CH_4) and non-methane volatile organic compounds (NMVOCs). As Hidy (2001) acknowledges, only recently it has been better understood that a great deal of aerosol precursor particles are produced by atmospheric chemical reactions. This takes place through the oxidation of sulfurous and nitrogenous gases and specific hydrocarbon vapors that give rise to very small particles. With widespread industrialization and urbanization, large amounts of these particles are emitted.[10] Reactive gases such as SO_2, NO_x and NMVOCs are main sources of particle production in the atmosphere. The formed sulfate aerosols enter the clouds, making them reflect more sunlight and creating a cooling effect on the atmosphere. It also brings lower solar radiation on the covering surface. This cooling effect is opposite to the global warming effect caused by GHGs, though regionally dependent near the industrial areas (NASA, 2017).[11] The cooling effect is calculated by Acosta-Navarro et al. (2017), who provide evidence that a reduction in aerosol emissions from fossil fuels following a maximum technically feasible reduction scenario brings a global and Arctic warming of 0.26 to 0.84 K, respectively. In contrast, fossil fuel emissions leading to the GHG effect—under the representative concentration pathway 4.5 emission scenario—would increase global and Arctic average surface temperature by 0.35 and 0.94 K, respectively.

We consider a sample of 23 OECD countries that includes Australia, Austria, Belgium, Canada, Switzerland, Chile, Germany, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Sweden, Turkey, the United Kingdom, and USA. We note that focusing on a sample of industrialized countries makes the use of time-series techniques appropriate for the analysis of convergence, since countries are likely to have already reached their steady states. However, according to Bernard and Durlauf (1996), time series tests of convergence are not suitable for developing countries located far from the steady state, because the data would not exhibit well-defined population moments. Notwithstanding, we can jointly capture the long-run and transition features of the data by exploiting both the time-series and cross-section dimension of the data—see Bernard and Durlauf (1996).

[7] The CEDS project is building a data-driven, open source framework to produce annual emission estimates of ten pollutants for research and analysis.

[8] According to the U.S. Environmental Protection Agency (2021), fossil fuel use and industrial processes (such as cement production and gas flaring) constitute the main sources of GHG emissions, with a 65% of global emissions in the U.S. Another 11% stems from CO_2 emissions related to deforestation and other land uses. Hence, about 76% of U.S. total emissions would correspond to CO_2 emissions.

[9] According to Hidy (2001), polar stratospheric clouds made up of sulfuric acid, nitric acid and water at very low temperatures, in combination with sunlight, lead to photochemical reactions of chlorine compounds which are responsible for the ozone-depleting phenomenon.

[10] A large part of these compounds is released when fossil fuel combustion (mainly coal and oil) takes place.

[11] In the industrialized world, ambitious programmes of installing flue gas desulfuration on electric power plants, the progressive removal of sulfur from crude oil and coal combustion, and the more recent ban of high sulfur bunker fuel in oceanic shipping have greatly reduced SO_2 emissions (Smith et al., 2011).

3.2 Empirical strategy

This paper follows the work by Strazicich and List (2003) for the case of stochastic convergence of per capita CO_2 emissions among OECD countries. Toward this end, we compute the logarithm of the ratio of the per capita emissions series relative to the average per capita emission levels of the specific pollutant for the sample of 23 OECD countries. Therefore, the variable of interest for unit root testing is relative emissions, i.e., $RE_{it} = \ln\left(CO_{2it}/\overline{CO_{2t}}\right)$, where $CO_{2_{it}}$ relates to per capita CO_2 emissions, and $\overline{CO_{2_t}}$ is the yearly sample average per capita CO_2 emission level, where $i=1,\ldots,N$ stands for the number of countries and $t=1,\ldots,T$ for the time periods. In our case, for most of the pollutants, N equals 23 and T equals 199, which makes a balanced panel of 4577 observations. For the other nine emission series, relative emissions are computed in the same way.

Expressing per capita emission levels relative to the sample average is equivalent to cross-sectionally demeaning the series, which controls for a very restrictive form of cross-correlation. In order to accommodate general forms of cross-dependence, we simulate the bootstrap critical values associated with the error structure of our panels of relative emissions via the Sieve bootstrap methodology (Chang, 2004). In short, stationarity in the log of relative emissions means that shocks affect only temporarily, such that individual country's per capita emissions converge stochastically toward the sample average. In contrast, a unit root in the log of relative per capita emissions means that shocks to the series affect permanently, which leads the emissions series to diverge from the sample average.

As Li and Papell (1999) point out, the concept of stochastic convergence implying the trend stationarity of the log of relative emissions constitutes a weak notion of convergence. This is due to the fact that it allows for permanent differences in per capita emission levels across countries through the presence of a linear trend in the deterministic component of the trend function. Li and Papell (1999) suggest a stronger notion given by deterministic convergence, implying mean stationarity in the log of relative emissions. This definition requires the elimination of both deterministic and stochastic trends, thus implying that emissions in one country move in parallel over the long-run relative to average emissions. Hence, deterministic convergence implies stochastic convergence, but not the other way around. For robustness purposes, we assess both time-series definitions of convergence.

3.3 Econometric notes

Let us assume a smooth transition specification for the relative per capita emission series:

$$y_{i,t} = \alpha_i + \beta_1 y_{i,t-1} + \beta_2 F\left(y_{i,t-1}, \theta_i, c_i\right) + \varepsilon_{i,t}$$

where $y_{i,t}$ is relative per capita emissions, $F(\cdot)$ is a transition matrix, θ_i represents the speed of transition between regimes, and c_i stands for a threshold parameter. In the case of an ESTAR model:

$$F\left(y_{i,t-1}, \theta_i, c_i\right) = 1 - \exp\left[-\theta_i\left(y_{i,t-1} - c_i\right)^2\right]$$

In the ESTAR model considered in the UO test, the coefficient on relative per capita emissions gradually changes depending on whether relative per capita emissions are close or far away from the equilibrium level, irrespective of whether this difference is positive or negative. Hence, when $\left(y_{i,t-1} - c_i\right) \to \pm\infty$ implying a very large deviation from equilibrium, the coefficient becomes $\beta_1 + \beta_2$, and when $y_{i,t-1} = c_i$ (i.e., there is no deviation), the coefficient is β_1. Positive and negative deviations from equilibrium revert to the equilibrium level at the same speed, thus implying symmetric nonlinear mean reversion. In the event of an AESTAR process, EO employs both an exponential function and a logistic function (in the way presented in the unpublished appendix) to capture asymmetric nonlinear mean reversion toward equilibrium across regimes. The combination of both specifications allows for asymmetric autoregressive adjustment either side of the attractor (c_i in this case) if the persistence parameters across regimes differ from each other.[12] Thus, the EO test allows for positive and negative deviations to revert to equilibrium at different speeds.

In the case of the LSTR model considered in the OHS test, we have:

$$F\left(\theta_i, c_i\right) = \frac{1}{1 + \exp\left[-\theta_i\left(t - c_i T\right)\right]}$$

The transition function $F\left(\theta_i, c_i\right)$ is continuous, bounded between zero and one, and controls the transition from one regime to another. In this case, the state variable is time. The parameter c_i entails the timing of the transition midpoint. The parameter θ_i implies the smoothness of transition. For small values of θ_i, $F\left(\theta_i, c_i\right)$ crosses the interval (0, 1) very slowly, and $F\left(\theta_i, c_i\right) = 0.5$ for all values of t in the limiting case that $\theta_i = 0$. For large values of θ_i, $F\left(\theta_i, c_i\right)$ changes from 0 to 1 instantaneously at time $t = c_i T$. Therefore, the logistic transition function nests the no-break and the instantaneous break model as a special case. As pointed out by LNV, this function is particularly appropriate when breaks take the form of large swings, thus capturing well the smooth and gradual processes relative to simple dummies.

The relevant coefficient takes different values depending on whether the series is below or above c_i. If $\left(t - c_i T\right) \to -\infty$, the model stays in the lower regime, whereas if $\left(t - c_i T\right) \to +\infty$, the model crosses to the upper regime. This specification aligns with an environmental policy aimed at reducing emissions where the level of response from environmental authorities varies with the magnitude of the structural break. Climate changes are changing as a smooth transition rather than sudden changes.[13]

The OSS test is based on univariate EL statistics; the latter adopting the LM detrending method and a flexible Fourier function form to allow for multiple smooth breaks. Since per capita emissions data cover a lengthy period of two centuries, this method is able to capture such multiple smooth changes over time. In the computations, multiple frequencies provide a more precise approximation than cumulative frequency which overfilters the data (see Shahbaz et al., 2019). All tests employ the Sieve bootstrap algorithms to allow for cross-sectional dependencies of unknown form. In Table 9 in the Appendix, we provide a summary of the tests and the processes involved.

[12] The AESTAR case nests the symmetric ESTAR specification if both parameters are equal.

[13] The fact that it exhibits a stationary structure around the long-term nonlinear trend indicates that emissions increase in a controlled way and that policy authorities can reduce their environmental effects by controlling this long-term smooth trend structure. Therefore, rejection of the unit root hypothesis in the OHS test informs policy authorities that they have enough time to control emissions and the need to reverse the dynamics of this smooth upward trend.

3.4 Advantages of nonlinear panel unit root tests

In convergence analysis, the use of nonlinear panel unit root tests is mandatory since they present the following advantages over linear tests previously employed in the emissions convergence literature. First, nonlinear tests are able to detect convergence even when the series are not near equilibrium, but in transition. Second, they allow for different convergence paths to differing steady states across units, thus capturing the probability of multiple equilibria. This contrasts with linear tests that would indicate that countries diverge as a whole. Third, when series gradually move to long-run equilibrium nonlinearly, linear unit root tests fail to detect convergence, thus favoring nonstationarity.

The ESTAR class of models exhibits the above advantages, but also allows for a high degree of heterogeneity, cross-sectional correlation, and asymmetry, if necessary, via the AESTAR model. The implied size nonlinearity entails that the speed of convergence increases when the distance from equilibrium rises. Finally, smooth transition models are also superior to threshold or Markov regime switching models, which impose abrupt changes on the coefficients, the switching variable and a priori function. Instead, smooth transition models allow for the choice of the appropriate switching variable and the type of transition function. The novelty of our study is that no previous work has applied this large battery of nonlinear panel unit root tests allowing for such rich nonlinear dynamics in the convergence analysis to such a large number of polluting compounds.

4 Results and discussions

As a preliminary check, we depict the log of relative per capita emissions for the ten pollutants under study. In Figures (A1) to (A10), shown in the unpublished appendix, we present the evolution of cross-country relative per capita emissions. On the one hand, there is a clear gradual narrowing of cross-country differences in per capita emissions over the long-run in the following pollutants: BC, CO_2, NMVOC, NO_x, and SO_2. This evidence points to converging dynamics among OECD emission levels for these compounds. In the case of carbon monoxide, there is a slight narrowing down of cross-country emission differences, while the graphical inspection does not show evidence of converging dynamics for CH_4, N_2O, NH_3 and OC compounds.

We now shift to formally study the existence of pollutants emissions convergence through the use of four recently developed nonlinear panel unit root tests allowing for state and time-dependence. We begin with the linear Chang (2004) panel unit root test, followed by the state-dependent nonlinear panel unit root tests of UO and EO, and the time-dependent panel tests of OHS and OSS. In addition to the panel statistics, we present the associated bootstrap p-values using the Sieve bootstrap methodology pioneered by Chang (2004). The results for each panel statistic are reported in a separate table, which contains the results for the specification with intercepts and linear trends (associated with stochastic convergence) in addition to the specification without trends (associated with the stronger notion of deterministic convergence). Once all tests are presented for each of the specifications, we will be able to infer which model characterizes each of the pollutants.

Table 2 Chang (2004) test

	Deterministic convergence (Only Intercepts)	Stochastic convergence (Intercepts and Trends)
Pollutant	$\bar{t}_C$	$\bar{t}_C$
BC Emissions	−0.809 (0.996)	−1.970 (0.875)
CH_4 Emissions	−1.220 (0.980)	−1.985 (0.945)
CO Emissions	−0.954 (0.989)	−1.586 (0.995)
CO_2 Emissions	−2.750 (0.005)***	−2.617 (0.070)*
N_2O Emissions	−1.451 (0.864)	−2.423 (0.308)
NH_3 Emissions	−1.139 (0.959)	−1.985 (0.870)
NMVOC Emissions	−0.876 (0.994)	−1.468 (0.996)
NO_x Emissions	−1.448 (0.726)	−2.338 (0.372)
OC Emissions	−0.802 (0.998)	−1.583 (0.995)
SO_2 Emissions	−1.188 (0.924)	−2.054 (0.802)

***, ** and * imply rejection of the unit root null at the 1, 5, and 10% significance level. Bootstrap p-values are given in parenthesis

4.1 Stochastic convergence

Table 2 reports the evidence from the application of the linear panel unit root test of Chang (2004). Remarkably, the joint unit root null is only rejected for CO_2 emissions at the 10% significance level. For the other nine pollutants, the evidence points to divergence among the 23 industrialized countries considered. Since the non-rejection of the unit root null with the linear panel test can be caused by the low statistical power in the presence of nonlinearities, we next apply four panel unit root tests allowing for different nonlinear dynamics. Table 3 presents the UO test based on symmetric ESTAR adjustment dynamics. The joint unit root null is rejected for six pollutants: N_2O and NO_x at the 1% significance level, CO_2 and SO_2 at the 5% level, and BC and CO at the 10% level. This evidence favors stochastic convergence for these six compounds. Table 4 reports the results from the more flexible EO panel statistic allowing for asymmetric ESTAR dynamics under the alternative hypothesis. The trend specification—associated with stochastic convergence—enables us to reject the joint nonstationarity null for seven of the ten per capita emissions series under study: CO_2 and NO_x emissions at the 1% level, BC, N_2O and SO_2 at the 5% level, and CO and NMVOC at the 10% level.

In Table 5 and 6, we present the time-dependent nonlinear tests of OHS and OSS, respectively. The former allows for a permanent structural break modelled by an LSTR function, and the latter allows for multiple smooth breaks through the flexible Fourier function. Models B and C in Table 5 incorporate a unit-specific deterministic trend, which only shifts in the latter case. In the case of the OHS panel statistic, the joint unit root null is rejected at conventional significance levels for only three pollutants: CH_4, CO_2 and N_2O. In the case of the OSS panel test, the joint nonstationarity null is rejected at the 5% level for N_2O emissions and at the 10% level for CO_2 emissions.

The upper panel of Table 7 presents the summary of results across all tests for the trend specification corresponding to the weaker notion of stochastic convergence. We consider the following general identification rules in the field to determine which specific model of

Table 3 Ucar and Omay (2009) Test: Panel ESTAR

	Deterministic convergence (Only intercepts)	Stochastic convergence (Intercepts and trends)
Pollutant	$\bar{t}_{UO}$	$\bar{t}_{UO}$
BC emissions	−1.329 (0.906)	−2.800 (0.080)*
CH_4 emissions	−1.625 (0.691)	−2.035 (0.909)
CO emissions	−1.207 (0.969)	−2.928 (0.075)*
CO_2 emissions	−3.322 (0.002)***	−3.167 (0.047)**
N_2O emissions	−1.595 (0.751)	−2.706 (0.009)***
NH_3 emissions	−1.331 (0.933)	−2.031 (0.845)
NMVOC emissions	−1.453 (0.837)	−2.344 (0.453)
NO_x emissions	−2.488 (0.027)**	−3.537 (0.001)***
OC emissions	−1.241 (0.965)	−1.998 (0.890)
SO_2 emissions	−1.739 (0.485)	−3.013 (0.029)**

***, ** and * imply rejection of the unit root null at the 1, 5, and 10% significance level. Bootstrap p-values are given in parenthesis those considered better captures the data generation process (DGP) of the stochastic converging dynamics for each pollutant. Firstly, if the pollutant series passes the linear unit root test, it is concluded that the convergence process can be considered linear stationary irrespective of other tests.[14] This appears to be the case of per capita CO_2 emissions. This finding supports the prevalent outcome in this literature favoring (linear) stochastic convergence in CO_2 emissions among industrialized countries.

Secondly, if the pollutant series is found to be stationary only by state-dependent tests, it means that the DGP has a state-dependent structure. The point to be considered in this structure is that the AESTAR test is the generalization of the ESTAR test, thus nesting it. If both tests render stationarity, then the process is determined by the symmetrical ESTAR test. If the ESTAR test could not render stationarity, but only the AESTAR test did, then the DGP of the sample is asymmetrical state-dependent. This is because if asymmetry is present, the ESTAR test cannot detect stationarity.[15] In the case of BC, CO, NO_x and SO_2 emissions, both UO and EO tests reject the nonstationarity null, which supports the ESTAR process as the model explaining converging dynamics. As regards NMVOC series, the EO test rejects the unit root null, whereas the UO test does not. This supports the AESTAR process in the converging dynamics of this series.

Thirdly, if the data render stationarity only in structural break tests, then the nonlinear structure or structural break takes place in the DGP according to time. The two time-dependent tests used have different properties. The OHS test with an LSTR model detects a single permanent structural break even if it is a smooth, sharp, or a different type of break. In contrast, the fractional frequency Fourier OSS test only captures smooth multiple structural breaks. Our results indicate that only CH_4 data incorporate the single sharp structural break in stochastic converging dynamics. In the case of the N_2O emissions data, the evidence is mixed since both state-dependent and time-dependent panel tests reject the null of nonstationarity. In other words, for this series state-dependent nonlinearity can be approximated by time-dependent nonlinearity. As for NH_3 and OC per capita emissions, the evidence points to divergence since all tests fail to reject the unit root null.

4.2 Deterministic convergence

We next assess whether there is evidence of a stronger notion given by deterministic convergence, which requires both deterministic and stochastic trends to be eliminated so that pollutant emissions in one country move in parallel to average emission levels over the long-run. As shown in Table 1, the linear Chang (2004) test only rejects the unit root null for CO_2 emissions. Concerning state-dependent panel unit root tests, the UO panel statistic –based on ESTAR adjustment dynamics– rejects the joint nonstationarity null for CO_2 emissions at the 1% level and NO_x at the 5% level. As regards the EO panel statistic based on AESTAR dynamics, the joint unit root null is rejected for six compounds: CO_2 and NO_x at the 1% level, BC, NMVOC and SO_2 at the 5% level, and CO at the 10% level. Concerning the time-dependent panel unit

[14] It is very likely that state-dependent and structural break tests confirm stationarity if the data are linear, since they maintain their statistical power in the case of linearity.

[15] In some cases, the symmetrical ESTAR test may show stationarity, but the AESTAR test does not. In these cases, the AESTAR test, which includes many parameters, cannot detect the symmetrical state-dependent structure because of the decrease in the degrees of freedom. In our study, such a situation was not encountered.

Table 4 Emirmahmutoğlu and Omay (2014) Test: Panel AESTAR

	Deterministic convergence (Only Intercepts)	Stochastic convergence (Intercepts and Trends)
Pollutant	$\overline{F}_{AE}$	$\overline{F}_{AE}$
BC emissions	5.654 (0.023)**	9.151 (0.011)**
CH_4 emissions	2.297 (0.728)	3.322 (0.709)
CO emissions	3.885 (0.098)*	5.544 (0.088)*
CO_2 emissions	11.520 (0.000)***	9.959 (0.004)***
N_2O emissions	2.268 (0.796)	5.180 (0.018)**
NH_3 emissions	2.190 (0.771)	3.334 (0.795)
NMVOC emissions	4.598 (0.039)**	5.361 (0.097)*
NO_x emissions	8.523 (0.007)***	10.492 (0.003)***
OC emissions	2.652 (0.507)	3.920 (0.503)
SO_2 emissions	5.374 (0.032)**	8.705 (0.013)**

***, ** and * imply rejection of the unit root null at the 1, 5, and 10% significance level. Bootstrap *p*-values are given in parenthesis

Table 5 Omay et al. (2018b) Test: Panel LSTR

	Model A Deterministic convergence	Model B Stochastic convergence	Model C Stochastic convergence
Pollutant	$\bar{t}_{\alpha}$	$\bar{t}_{\alpha(\beta)}$	$\bar{t}_{\alpha\beta}$
BC emissions	−2.808 (0.572)	−2.866 (0.823)	−3.213 (0.952)
CH_4 emissions	−2.992 (0.143)	−3.442 (0.098)*	−3.857 (0.000)***
CO emissions	−2.307 (0.952)	−2.688 (0.999)	−3.389 (0.872)
CO_2 emissions	−3.139 (0.145)	−3.800 (0.000)***	−4.263 (0.020)**
N_2O emissions	−2.989 (0.242)	−3.485 (0.000)***	−3.941 (0.006)***
NH_3 emissions	−2.224 (0.990)	−2.571 (0.891)	−2.770 (0.829)
NMVOC emissions	−1.885 (0.999)	−2.276 (0.999)	−2.646 (0.956)
NO_x emissions	−3.038 (0.206)	−3.202 (0.906)	−3.815 (0.224)
OC emissions	−2.344 (0.973)	−2.734 (0.998)	−3.363 (0.828)
SO_2 emissions	−2.383 (0.954)	−2.687 (0.995)	−3.091 (0.992)

***, ** and * imply rejection of the unit root null at the 1, 5, and 10% significance level. Bootstrap p-values are given in parenthesis

Table 6 Omay et al. (2021b) Test: Panel Fourier

	Deterministic convergence (Only Intercepts)	Stochastic convergence (Intercepts and Trends)
Pollutant	$\bar{t}_{FIPS}$	$\bar{t}_{FIPS}$
BC emissions	−2.082 (0.872)	−2.824 (0.960)
CH_4 emissions	−2.235 (0.871)	−3.319 (0.222)
CO emissions	−1.586 (0.995)	−2.577 (0.991)
CO_2 emissions	−2.576 (0.125)	−3.478 (0.070)*
N_2O emissions	−2.284 (0.846)	−3.501 (0.022)**
NH_3 emissions	−1.589 (0.997)	−2.422 (0.995)
NMVOC emissions	−1.601 (0.995)	−2.252 (0.998)
NO_x emissions	−2.521 (0.355)	−3.202 (0.497)
OC emissions	−1.754 (0.987)	−2.508 (0.992)
SO_2 Emissions	−1.803 (0.973)	−2.888 (0.933)

***, ** and * imply rejection of the unit root null at the 1, 5, and 10% significance level. Bootstrap p-values are given in parenthesis

root tests, both OHS and OSS panel statistics fail to reject the joint nonstationarity null, thus favoring the lack of deterministic convergence for all the pollutants under study.

Using the same identification rules as above, there is evidence of linear deterministic convergence dynamics for CO_2 emissions, since the linear Chang (2004) test rejects the unit root null irrespective of what the other tests do. In the case of per capita NO_x emissions, both state-dependent panel tests reject the unit root null, in which case the deterministic converging dynamics of the series are characterized by symmetric ESTAR adjustment. Concerning BC, CO, NMVOC and SO_2 per capita emissions, the unit root is rejected with the EO test but not with the UO test. Hence, these four compounds series exhibit deterministic convergence with AESTAR adjustment dynamics. As in the stochastic convergence analysis, NH_3 and OC emissions do not exhibit deterministic convergence either, —not surprisingly given that this notion is more difficult to achieve. In fact, CH_4 and N_2O appeared to converge stochastically, but not deterministically.

5 Conclusion

This article has assessed the existence of stochastic and deterministic convergence among a panel of 23 OECD countries for ten series of annual estimates of anthropogenic emissions that include aerosols, aerosol precursor and reactive compounds, and carbon dioxide over the period 1820–2018. For that purpose, we have applied four state-of-the-art panel unit root tests that allow for several forms of time-dependent and state-dependent nonlinearity. Our evidence has favored stochastic convergence following a linear process for CO_2, whereas the adjustment is nonlinear for BC, CO, CH_4, NMVOC, N_2O, NO_x and SO_2. In contrast, NH_3 and OC emissions have diverged. Concerning deterministic convergence, CO_2 converges linearly, while BC, CO, NO_x, NMVOC and SO_2 adjust nonlinearly.

The type of DGP followed by the different compounds can provide some helpful specific clues for policymaking. In the case of stochastic convergence, for NMVOC the existence

Table 7 Summary table

Pollutant	Linear	State dependent nonlinearity		Structural breaks		
	Chang	UO (ESTAR)	EO (AESTAR)	OHS (LSTR)	OSS (Fourier)	DGP
Stochastic Convergence						
BC emissions		+	+			ESTAR
CH_4 emissions				+		LSTR Break
CO emissions		+	+			ESTAR
CO_2 emissions	+	+	+	+	+	Linear
N_2O emissions		+	+	+	+	Mixed Evidence
NH_3 emissions						Non-stationary
NMVOC emissions			+			AESTAR
NO_x Emissions		+	+			ESTAR
OC emissions						Non-stationary
SO_2 emissions		+	+			ESTAR
Deterministic Convergence						
BC emissions			+			AESTAR
CH_4 emissions						Non-stationary
CO emissions			+			AESTAR
CO_2 emissions	+	+	+			Linear
N_2O emissions						Non-stationary
NH_3 emissions						Non-stationary
NMVOC emissions			+			AESTAR
NO_x emissions		+	+			ESTAR
OC emissions						Non-stationary
SO_2 emissions			+			AESTAR

Note: + indicates that the pollutant rejects the null of non-convergence for each specific panel unit root test of asymmetric regimes carries important information content for the environmental policy authorities of OECD countries. While the upward trend is low in low regimes as given by the autoregressive parameter, tendency to converge increases in high regimes since the autoregressive parameter is high. Thus, when there is AESTAR-type convergence, it is necessary to take more severe emissions abatement measures for the lower regime, while even the most insignificant policy change for the upper regime will increase the convergence rate.

As there is no asymmetric effect in the data in the linear and ESTAR tests, policy differentiation will not be required. Hence, the continuation of policies are warranted for CO_2 in the linear case, as well as for BC, CO, NO_x and SO_2 in the ESTAR case. In the latter four compounds, a large deviation from equilibrium—irrespective of its sign—will speed up convergence to cross-country average emission levels. In the case of CH_4 emissions with convergence driven by LSTR nonlinearity capturing a permanent break, environmental policy targeting emissions cuts will be compatible with a level of response by environmental authorities that varies with the magnitude of the structural break. The fact that it exhibits a stationary structure around the long-term nonlinear trend indicates that CH_4 emissions rise in a controlled way and that policy authorities can reduce their environmental effects by controlling this long-term smooth trend structure. Thus, this implies that policy authorities have sufficient time to control emissions and reverse the dynamics of this smooth upward trend.

The general policy implications of our results are as follows. With the exception of NH_3 and OC emissions for which even the weaker notion of convergence does not hold,[16] the finding of stochastic emissions convergence among industrialized countries points to the feasibility to achieve SGD13 of the 2030 Agenda and the targets of the Paris Agreement. Also, evidence of convergence backs up the application of a per capita emissions allocation scheme without resorting to significant resource transfers through international emissions trading or cross-border movements of high-pollution industries. In addition, emissions convergence facilitates the harmonization of legislation targeting anthropogenic emissions abatement. Hence, emissions convergence in the industrialized world makes it easier to convince large emitting countries like China and India to control and reduce their emissions. Furthermore, the convergence assumption is a key part in most projection models guiding policymakers in their emission abatement policies to combat climate change.

To conclude, given that energy-related emissions constitute a large proportion of total emissions, it is key to speed up the decarbonization of the countries' energy systems through the expansion of infrastructure and upgrade of renewable energy technologies associated with solar, geothermal, wind, hydropower and biomass sources, in addition to raising energy efficiency to make clean energy more affordable and accessible to all.

A possible limitation of this study is that the authors have not developed yet appropriate hybrid panel unit root test statistics that combine state-dependence exhibited by the ESTAR class of models and time-dependence in the form of single or multiple sharp or smooth changes. Hence, an avenue of research that we will follow in the future is to develop these hybrid panel unit root tests, which will be extensions of the univariate nonlinear hybrid unit root tests of Christopoulos and Leon-Ledesma (2010), Omay and Yıldırım (2014) and Omay et al. (2018a), which combine a structural break(s) function form with symmetric and asymmetric ESTAR adjustment. Once the

[16] For these two compounds, the adoption of the best management standards worldwide, ISO 14001, would be helpful to control emissions and harmonize environmental legislative efforts that would facilitate emissions convergence. As a matter of fact, Abid et al. (2021) and Abid et al. (2022) provide evidence of the positive impact that the adoption of ISO 14001 in Pakistan has had on environmental sustainability and green growth.

hybrid panel unit root tests are developed, it will be worth applying them to investigate emissions convergence for panel data disaggregated at several levels: 1) sectoral analyses following the work by Brännlund et al. (2015) and Yu et al. (2018), 2) regional or state-level analyses following the work by Burnett (2016), Ivanovski and Awaworyi-Churchill (2020) and Tiwari et al. (2021), 3) analyses of sectors and regions together following the work by Wang and Zhang (2014) and Bolea et al. (2020), 4) regional trade groupings analyses following the work by Apergis and Payne (2020) and Yilanci and Korkut-Pata (2020), and 5) analyses of the components of emissions such as coal, oil and natural gas following Haider and Akram (2019).

6 Code and data availability

Codes for the computation of the statistics are embedded in the following online page ran from one of the authors (Prof. Tolga Omay) accessible at https://tolgaomay.shinyapps.io/Non-Stat_Panel_Unit_Root_Test/. The data on pollutant emissions are freely available at http://www.globalchange.umd.edu/CEDS/ and population figures at https://www.rug.nl/ggdc/historicaldevelopment/maddison/.

Appendix

See Tables 8 and 9

Table 8 Data sources and description

Pollutant Emissions	Unit of Measurement	Years Available	Description	Data Sources
BC (black carbon)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
CH_4 (methane)	Thousand metric tons (kt)	1970–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
CO (carbon monoxide)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/

Table 8 (continued)

Pollutant Emissions	Unit of Measurement	Years Available	Description	Data Sources
CO_2 (carbon dioxide)	Thousand metric tons (kt)	1851–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
N_2O (nitrous oxide)	Thousand metric tons (kt)	1970–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
NH_3 (ammonia)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/

Table 8 (continued)

Pollutant Emissions	Unit of Measurement	Years Available	Description	Data Sources
NMVOCs (non-methane volatile organic compounds)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
NO_x (nitrogen oxides)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/
OC (organic carbon)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/

Table 8 (continued)

Pollutant Emissions	Unit of Measurement	Years Available	Description	Data Sources
SO_2 (sulfur dioxide)	Thousand metric tons (kt)	1820–2018	Per capita emission levels	CEDS Database for Historical Emissions (Hoesly et al., 2018), version v_2021_02_05 (O'Rourke et al., 2021). http://www.globalchange.umd.edu/CEDS/. Long-term population data from the Maddison Project Database (2020), https://www.rug.nl/ggdc/historicaldevelopment/maddison/

Table 9 Linear and nonlinear models

Structure	Linear	State dependent		Structural breaks	
Test	Chang Test	UO Test	EO Test (AESTAR)	OHS Test (LSTR)	OSS Test (Fourier)
Function	AR(1)	ESTAR(1)	AESTAR(1)	LSTR	Fourier
Testing model	$\Delta y_{i,t} = \alpha_i + \phi_{1i} y_{i,t-1}$	$\Delta y_{i,t} = \alpha_i + \phi_{1i} y_{i,t-1} G(.)$	$\Delta y_{i,t} = \alpha_i + G(.)\left[S(.)\rho_{1i} + (1 - S(.))\rho_{2i}\right] y_{i,t-1}$	$\Delta y_{i,t} = \alpha_i + \theta_1(t) + \phi_{1i} y_{i,t-1}$	$\Delta y_{i,t} = \alpha_i + \theta_2(t) + \phi_{1i} y_{i,t-1}$
Functional forms		$G\left(y_{i,t-1}, \theta_i\right) = 1 - exp\left[-\theta_i\left(y_{i,t-1}\right)^2\right]$	$G\left(y_{i,t-1}, \theta_{1i}\right) = 1 - exp\left[-\theta_{1i}\left(y_{i,t-1}\right)^2\right]$ $S\left(y_{i,t-1}, \theta_{2i}\right) = \frac{1}{1+exp\left[-\theta_{2i}\left(y_{i,t-1}\right)\right]}$	$F\left(\theta_{3i}, c_i\right) = \frac{1}{1+exp\left[-\theta_{3i}\left(t-c_i T\right)\right]}$ $A)\ \theta_1(t) = a_0 + a_1 F(.)$ $B)\ \theta_1(t) = a_0 + a_1 F(.) + b_0 t$ $C)\ \theta_1(t) = a_0 + a_1 F(.) + b_0 t + b_1 t F(.)$	$\theta_2(t) = \beta_1 + \beta_2 \sin(.) + \beta_3 \cos(.)$ $\sin(.) = sin\left(\frac{2\pi kt}{T}\right)$ $cos(.) = cos\left(\frac{2\pi kt}{T}\right)$
Linearized versions		$\Delta y_{i,t} = \alpha_i + \phi_{1i} y_{i,t-1}^3$	$\Delta y_{i,t} = \alpha_i + \phi_{1i} y_{i,t-1}^3 + \phi_{2i} y_{i,t-1}^4$		
Additional notes	Speed of convergence is constant, irrespective of the distance from equilibrium	The coefficient on $y_{i,t-1}$ changes depending on whether this variable is close or far away from the equilibrium level, regardless of whether this difference is positive or negative Hence, positive and negative deviations from equilibrium revert to the equilibrium level at the same speed of convergence Symmetric size nonlinearity	Positive and negative deviations from equilibrium exhibit different speeds of mean reversion The speed of convergence depends on whether $y_{i,t-1}$ is above or below the steady state as well as on the distance from equilibrium Asymmetric size nonlinearity	It allows for a single permanent break through an LSTR model that models a smooth transition from one trend function to another, with the limitation that only captures one break Structural break nonlinearity	Flexible Fourier function form that allows for multiple smooth breaks For selecting the appropriate Fourier frequency, we use multiple frequencies to provide a more precise approximation vs. cumulative frequency Structural break nonlinearity

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Declarations

Conflicts of interests The authors declare that they do not have any relevant financial or non-financial interests to disclose.

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