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US CO_2 emissions and IPCC components: Evidence of persistence using fractional integration[☆]

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ABSTRACT

This paper investigates the persistence of CO_2 emissions in the US and per Intergovernmental Panel on Climate Change (IPCC) category contribution, evaluating its persistence across time (1970–2022). The structure of the integration factor and major structural breaks are examined to determine the degree of persistence across sectors and to assess policy effectiveness. Empirical results show clear evidence of persistence and non-mean reversion patterns in the long-term CO_2 emissions in all sectors; though, log-data show weak mean reversion across global bioenergetic emissions and fossil manufacturing-civil airline emissions. Moreover, structural breaks results suggest that these breaks are mostly related to economic shocks rather than to environmental policies. Excepting Road and Transportation, all IPCC sectors show decreasing emission patterns since 2000. Thus, this persistent profile would suggest that emissions from these sectors would maintain this decreasing pattern in the future. However, Road and Transportation (29 % of total emissions) exhibit a different growing pattern, that suggests further increases if no additional measures are taken. Therefore, to accomplish IPCC commitments, more efforts are recommended with a special focus in the Road and Transportation sector to change the long-term US CO_2 emission pattern.

1. Introduction

Exposure to air pollution causes seven million premature deaths each year worldwide (World Health Organization, 2021) and the cost of health damage amounts to US$8.1 trillion per year, equivalent to 6.1 % of global GDP (World Bank, 2022). This concern has led certain organizations such as the IMF to include climate data as part of the macroeconomic indicators of countries (IMF, 2023).

The European Commission Report (2023) on global greenhouse gas (GHG) emissions points to China, the US, India, the EU27, Russia and Brazil as the six major contributors, accounting for 61.6 % of global emissions in 2022, with the US being the second most polluting country in the world after China. Almost half of all CO_2 planet emissions are produced between these two nations according to the Global Carbon Atlas (2022).

Climate change caused by emissions and the associated greenhouse effect not only impact health (Nakhli et al., 2022), but also lead to extreme events such as tornadoes, hurricanes, heatwaves, and fires, among others. In fact, the US has suffered 363 weather and climate disasters since 1980 and their total cost has exceeded 2590 billion dollars (NOAA, 2023). Concerns about climate change and its effects has led Joe Biden's administration to pass a series of regulations to try to reduce the

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emission of polluting gases (The Inflation Reduction Act, The White House, 2023). The Department of Energy (Renewable Energy Magazine, 2023) announced in June 2023 an investment of $135 million for 40 research projects aimed at reducing energy use and emissions from the industrial sector. In March 2024, $6 billion was approved for projects to reduce CO_2 emissions in the industrial sector. This is the largest investment in U.S. history aimed at combatting climate change (AP, 2024).

In the United States, emissions from both fossil fuels and organic sources significantly contribute to the overall GHG profile (Xu et al., 2022). In 2022, total US GHG emissions amounted to approximately 6343 million metric tons of CO_2 equivalents, with fossil fuel burning being a major contributor (Blasing et al., 2005; Gurney et al., 2009; Jackson et al., 2020 among others). In fact, Hannah (2019) point out that since 1751, the US has emitted more CO_2 than any other country (approximately 400 billion tons) and accounts for 25 % of total historical emissions. The largest pollutant in the US in terms of emissions and impact on air quality is CO_2 which accounts for 79.7 % of GHG emissions (EPA, 2024a,b,c). Thus, it is relevant to study what the main CO_2 emission sources are in order to a develop suitable environmental policies able to meet recent Intergovernmental Panel on Climate Change (IPCC) agreements of reducing CO_2 emissions to net zero (around 2050) and limit global temperature increases below 1.5 °C by 2100 (IPCC, 2018).

The IPCC distinguishes between the slow domain of the carbon cycle, where turnover times exceed 10,000 years, and the fast domain, which includes the atmosphere, ocean, vegetation, and soil. In the fast domain, vegetation has turnover times ranging from 1 to 100 years, while soil carbon turnover times range from 10 to 500 years (IEA, 2024a). Fossil fuel transfers carbon from the slow domain to the fast domain, while bioenergy systems operate within the fast domain. According to the EDGAR v8.0 database (Crippa et al., 2023), fossil fuels are the main contributor of CO_2 emissions in the US (88 %). Although CO_2 emissions from fossil fuel combustion increased by about 1 % in 2022 compared to the previous year due to the post-COVID-19 recovery (Alava and Singh, 2022; Deng et al., 2024), emissions in the US have decreased by 13 % after peaking in 2000. However, between 1970 and 2000, there was a rise of 30 % and therefore, emissions should decrease much more to reach previous levels. Following the IPCC 2006 standards, Table 1 summarizes the sector contributors to US CO_2 emissions, while Table 2 outlines growth patterns between the periods 1970–2000 and 2000–2022. Fig. 1 graphically illustrates this evolution. In the US, Electricity and Heat generation (31.5 %) and Road Transportation (28.9 %) are currently the largest contributors to greenhouse gas emissions. However, since 2000, emissions from Electricity generation have significantly decreased by 35 %, while Road Transportation emissions have remained relatively stable, increasing by 7 %.

Other major contributors are Manufacturing Industries (13.3 %) and Residential (12.9 %) that also contribute to GHG emissions through direct and indirect means (Lee and Lee, 2014; Danylo et al., 2019). Direct emissions include those from the combustion of natural gas and petroleum products for heating and cooking, while indirect emissions arise from electricity use (Pistochini et al., 2022). However, these sectors had significantly reduced their relative weight in comparison to 1970 (46 %–26 %). In the case of manufacturing there has been a global shift of energy intensive industries away from historical centers in the US and Europe to developing regions such as China, explaining reductions of industry emissions (Lamb et al., 2021). Furthermore, improvements in the energy efficiency of material extraction, processing and manufacturing have reduced both industrial and residential energy use per unit of output (Wang et al., 2019). On the other hand, the major growth sectors are Gas, which has increased by 984 % since 2000, and Water Navigation, which has grown by 229 %. However, the combined importance of these sectors is still limited to less than 4 % of the total.

Thus, while the United States has made progress in reducing emissions from certain sectors, the continued use of fossil fuels and organic waste processes remain significant sources of GHG emissions in comparison with 1970 and the year 2000 (Huisingh et al., 2015). Efforts to mitigate these impacts include transitioning to renewable energy sources, improving waste management practices, and improving energy efficiency across sectors (Ganda and Ngwakwe, 2014).

The objective of this paper is to discover the long-term pattern of these emissions and check if these are expected to be corrected naturally, showing mean reversion properties in the long term, or if, on the other hand, additional policies are needed. This approach provides a country-level emissions perspective rather than an industry-specific focus. As a novel approach, we aim to conduct a more in-depth analysis of emissions within the US to identify which sectors need to improve. To complement this study and assess the effectiveness of the policies implemented, we will analyze the existence of structural breaks (Bai and Perron, 2003) to identify long-term trend changes in the data. These changes should theoretically be linked to the application of successful policies.

Therefore, our purpose is to determine whether current environmental policies are effective and to support the design of new, targeted policies to reduce major pollutants, such as CO_2. Empirical results will show clear evidence of non-mean reversion patterns in CO_2 emissions in the long-term in all sectors; however, log-data shows weak mean reversion across global bioenergetic emissions and fossil manufacturing-civil airline emissions. Additionally, evidence will be presented of an important long-term correlation between the two largest fossil contributors (Heat/Electricity and Road and Transport), supporting the hypothesis that specific policies focused in these two sectors would generate a significant reduction in the volume of total emissions. Finally, when checking structural breaks, results would suggest that these significant changes are mostly related to economic shocks rather than to environmental policies.

To sum up, the contribution of this paper is twofold. First, it provides more extensive evidence regarding the roots of US CO_2 emissions persistence and also on whether or not these emissions and their IPCC components are mean reverting. Second, it adopts an econometric

Table 1
US CO_2 emissions data in Gg (1970 and 2022).

		2022	1970		2022	
ipcc_code_2006	**ipcc_code_2006_name**	Gg	Weight 1970	Fossil/total	Weight 2022	Fossil/total
1.A.1.a	Main Activity Electricity and Heat Production	1,681,460	22.9 %	100.0 %	31.5 %	96.2 %
1.A.1.bc	Petroleum Refining - Manufacture of Solid Fuels and Other Energy Industries	256,330	6.2 %	100.0 %	4.8 %	99.9 %
1.A.2	Manufacturing Industries and Construction	709,249	27.6 %	84.7 %	13.3 %	65.8 %
1.A.3.a	Civil Aviation	161,449	2.8 %	100.0 %	3.0 %	100.0 %
1.A.3.b_noRES	Road Transportation no resuspension	1,542,535	17.2 %	100.0 %	28.9 %	92.8 %
1.A.3.c	Railways	37,836	0.8 %	100.0 %	0.7 %	95.6 %
1.A.3.d	Water-borne Navigation	32,522	0.3 %	100.0 %	0.6 %	98.6 %
1.A.3.e	Other Transportation	58,865	0.8 %	100.0 %	1.1 %	100.0 %
1.A.4	Residential and other sectors	686,438	18.5 %	97.6 %	12.9 %	85.2 %
1.A.5	Non-Specified	1551	1.6 %	43.3 %	0.0 %	100.0 %
1.B.1	Solid Fuels	14,716	0.8 %	100.0 %	0.3 %	100.0 %
1.B.2	Oil and Natural Gas	149,815	0.3 %	100.0 %	2.8 %	11.0 %

Table 2
US CO_2 emissions evolution per sector in Gg (1970, 2000 and 2022

ipcc_code_2006_for_standard_report_name	1970	2000	growth (1970–2000)	2022	growth (2000–2022)
Main Activity Electricity and Heat Production	1,082,356	2,608,208	141 %	1,681,460	−36 %
Petroleum Refining - Manufacture of Solid Fuels and Other Energy Industries	294,892	259,746	−12 %	256,330	−1 %
Manufacturing Industries and Construction	1,303,610	782,675	−40 %	709,249	−9 %
Civil Aviation	132,256	203,803	54 %	161,449	−21 %
Road Transportation no resuspension	813,900	1,445,355	78 %	1,542,535	7 %
Railways	39,178	30,856	−21 %	37,836	23 %
Water-borne Navigation	14,820	9873	−33 %	32,522	229 %
Other Transportation	39,628	37,409	−6 %	58,865	57 %
Residential and other sectors	872,751	721,566	−17 %	686,438	−5 %
Non-Specified	73,963	5993	−92 %	1551	−74 %
Solid Fuels	36,096	21,979	−39 %	14,716	−33 %
Oil and Natural Gas	15,218	13,819	−9 %	149,815	984 %
Total	4,718,668	6,141,285	30 %	5,332,766	−13 %

approach that is more flexible than the unit root testing generally carried out in previous studies on this topic. The rest of the paper is structured as follows: Section 2 provides a brief review of the relevant literature; Section 3 outlines the fractional integration approach used for the analysis; Section 4 describes the data and discusses the empirical results; Section 5 offers some concluding remarks.

2. Literature review

Recent literature on air pollution and its consequences in the US can be found in Bevan et al. (2021), Malik et al. (2022), Remigio et al. (2022), and Liu et al., (2023) among many others, while studies analysing CO_2 emissions and their effects include, among others, Sharif et al. (2021), Pata (2021), Magazzino et al. (2021) and Mutascu (2022). Traditional analyses in environmental research have typically relied on stationarity I(0) and non-stationary I(1) dichotomy, with unit root testing. For instance, Christidou et al. (2013) analyzed the stationarity of carbon CO_2 emissions per capita for a global set of 36 countries (1870–2006, yearly data) by applying non-linear unit root tests and finding evidence that stationarity is more likely in richer countries that outsourced some of the intensive emission industries. Later on, Tiwari et al. (2016) analyzed with non-linear unit root tests the per capita CO_2 emissions for 35 countries in Sub-Saharan Africa (1960–2009, annual data) confirming this empirical evidence of stationarity now for developing countries. Longer spans for global CO_2 emissions (0 b.C. – 2014, annual data) were used in Erdogan et al. (2022), finding evidence of unit roots in the whole series, with structural breaks during the influenza pandemic (1557) and the invention of the steam engine (1712). Apergis and Payne (2017) studied the convergence of the per capita CO_2 emissions (1980–2013, yearly samples) by examining the 50 US states by sector, and by fossil fuel source, with evidence of multiple equilibria and distinctive convergence paths associated with each cluster of states. More recently, Pata and Aydin (2023) used a new wavelet-based non-linear unit root test to investigate the per capita CO_2 emissions (1868–2014 period, annual data) for the G7 countries, finding evidence that CO_2 emissions have a unit root for all countries, and therefore concluding that CO_2 emission policies have permanent effects for G7 countries.

However, it has become apparent that unit root tests do not provide reliable evidence. For instance, Diebold and Rudebush (1991) and Hassler and Wolters (1994) examined the properties of the Dickey-Fuller tests under fractionally integrated alternatives and showed that they have low power under this type of alternatives. Similarly, Lee and Schmidt (1996) examined the KPSS tests and found evidence of unbiasedness only against stationary long memory alternatives or $0 < d < 0.5$. The issue is that imposing a dichotomy between I(0) and I(1) behaviour is very restrictive as many series exhibit long memory and are non-stationary but still mean-reverting, which occurs if the differencing parameter is in the range [0.5, 1). In such cases, fractional integration is the most appropriate modelling framework as standard unit root tests would lead to the incorrect conclusion that such series exhibit unit roots. Therefore, fractional integration is a methodology that extends the dichotomy between stationary and non-stationary series as it allows the estimation of the integration parameter and lets it take any real value, including fractional ones. When measuring persistence, the higher the differencing parameter d is, the higher the association is between the observations and the past dependence in the data, shedding light on whether or not it is mean reverting (Caporale et al., 2024). Thus, it provides gradual information on whether the effects of shocks to the series will be transitory or permanent which cannot be found in other studies using different methods such as unobserved components (Koopman and Ooms, 2003).

Regarding the CO_2 emission studies using fractional integration estimations, only a few cases arise. Gil-Alana et al. (2017) analyzed the long-term behavior of CO_2 emissions for the BRICS and G7 countries (for the last 150–250 years), finding significant differences in terms of the degree of industrialization. In particular, most series display orders of integration equal to or higher than one implying permanent effects of shocks in CO_2 emissions. Gil-Alana and Trani (2019) studied most EU members, China and the US (1960–2013 with yearly samples), finding evidence of significant positive trends and explosive behavior (i.e., $d > 1$) in most southern countries (Spain, Italy, Greece and Bulgaria). After this, Gil-Alana and Monge (2020), analyzed worldwide CO_2 emissions (1880–2015 with yearly samples) in terms of the temperature deviations, and obtained a CO_2 integration factor of 1.30 throughout the entire period of analysis. A different approach was taken on Claudio-Quiroga and Gil-Alana (2022) that used daily data and only two years of CO_2 emissions for G7, EU27 and BRICS countries during the COVID19 pandemic period (2019–2020). Contrary to other studies, these authors found evidence of mean reversion in all countries as the integration factor ranged between $0.5 < d < 1$ in all series, maybe due to its short-term behavior. Finally, Infante et al. (2024) analyzed CO_2, CH_4, and NO_2 pollutants, with monthly data starting in January 2000 and ending in December 2021 from major European countries, the US, Japan, Brazil, China, and India for comparison purposes with developing countries. Empirical results show clear evidence of mean reversion in CO_2 emissions across all countries, indicating certain degrees of stabilization. However, in terms of other pollutants such as CH_4, and NO_2 not all countries exhibit mean reversion properties.

Recent research has expanded the scope of US CO_2 emissions analysis, incorporating various factors and methodologies. Basu et al. (2020) estimated US fossil fuel CO_2 emissions using measurements of Carbon-14 in atmospheric CO_2. On the other hand, Bennedsen et al. (2021) developed models for forecasting and nowcasting US CO_2 emissions using multiple macroeconomic predictors. Sector-specific studies by Charles et al. (2024) and Durga et al. (2024) focused on the pulp and paper, and iron and steel industries, respectively, in achieving net-zero US CO_2 emissions by 2050. With regard to the relationship between economic factors and emissions, Syed and Bouri (2022) investigated the impact of economic policy uncertainty on US CO_2

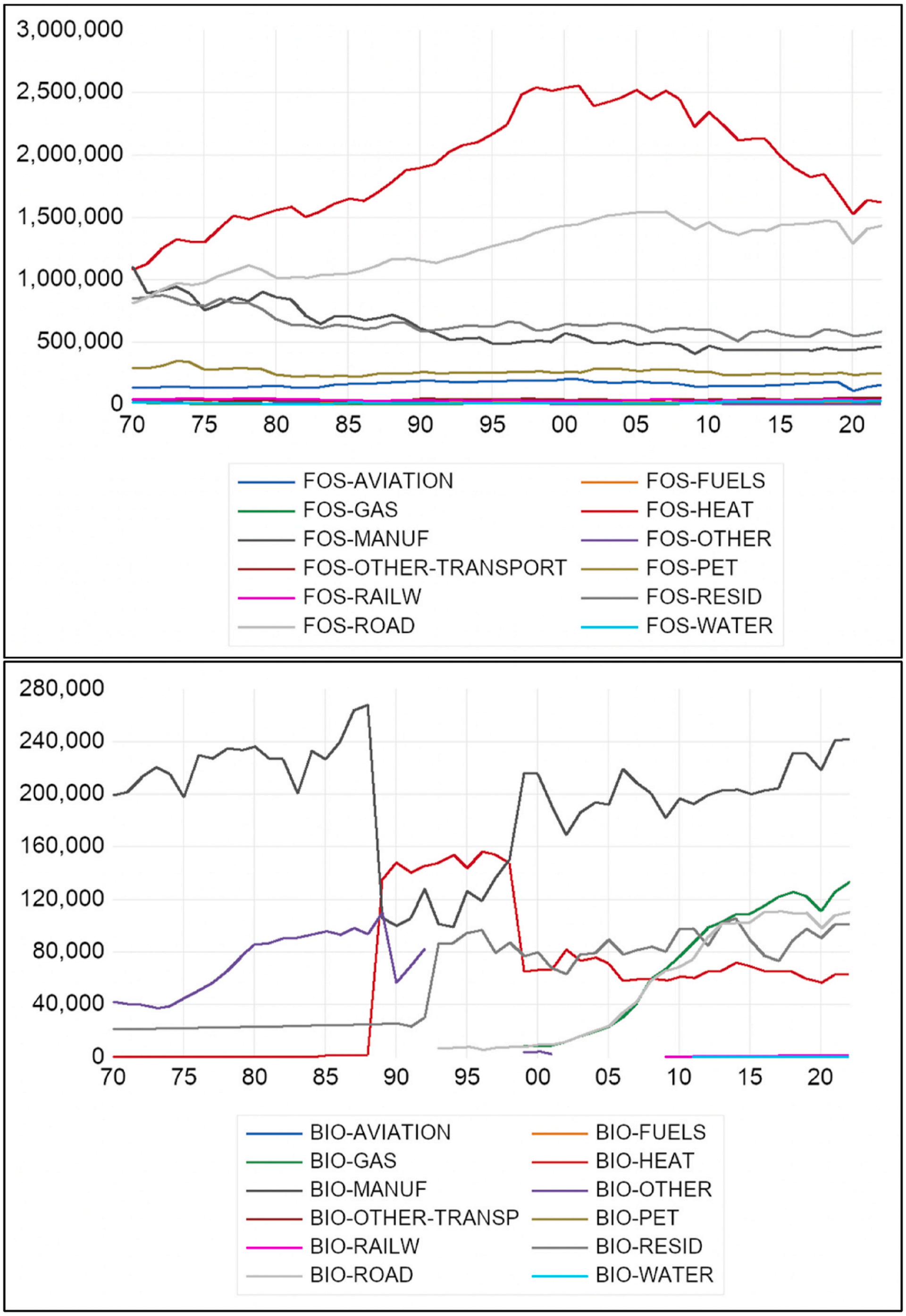

Fig. 1. Main contributors of US CO2 (fossil and biogenic) emissions in Gg. Data from EDGAR v8.0.

emissions while Jeon (2022) examined the relationship between CO_2 emissions, renewable energy, and economic growth. Kanas et al. (2023) explored the connection between systemic risk and CO_2 emissions, adding an interesting financial perspective to environmental research. Finally, it is important to note that innovative methodologies continue to emerge. For instance, Kassouri et al. (2022) used wavelet-based models to study oil shocks and emissions while Ma et al. (2023) resolved carbon-climate feedback in Alaskan wetlands. These diverse approaches are expected to contribute to a more comprehensive understanding of emission dynamics and their implications for climate policy.

As research in this field advances, it becomes increasingly clear that integrating these diverse methodologies and perspectives is an essential point for developing effective strategies for emission reduction and climate change mitigation. For instance, the evolution from simple unit root tests to complex fractional integration models and multifaceted approaches has allowed for a more nuanced understanding of emission dynamics, persistence, and the impacts of various economic and policy factors. In this paper, we integrate this approach with a deeper analysis for US IPCC CO_2 contributors. Therefore, the major innovations of this paper are first, to lay out a better econometric approach for measuring persistence in the field of CO_2 emissions; and second, to make a more thorough persistence study into the different US IPCC contributors as these have been aggregated in previous papers.

3. Data and methodology

The datasheet of this paper is built with data taken from Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL) from the Emissions Database for Global Atmospheric Research - EDGAR, release 8.0 (Crippa et al., 2023). Time series were chosen for CO_2 with yearly observations starting in 1970 and ending in 2022. Selected sectors were chosen with a larger weight of 1.5 % from total emissions. Therefore, fossil and biogenic emissions from Manufacturing (13.3 %), Residential (12.9 %) and Oil and Gas (2.8 %) were chosen; as were fossil emissions from Electricity and Heat generation (31.5 %), Civil airline (3.0 %), Railways (0.8 %), Road transport (28.9 %) and Petroleum refining (4.8 %). The group Rest of Sectors accounted for less than 3 % and were included in the total emissions for both fuel and biogenic categories. Table 3 summarizes the main descriptive statistics of the selected data.

The methodology employed in this paper is fractional integration, a specific modelling framework within the category of long memory processes, named for the high degree of association between observations that are widely separated in time. Fractional integration is characterized because the number of differences required in a series to render it stationary I(0) or short memory is a non-integer positive value. Thus, a series x(t), t = 1, 2, …is said to be fractionally integrated or integrated of order d if it admits the following representation,

$$(1-\mathrm{L})^{\mathrm{d}}\ \mathrm{x}(\mathrm{t}) = \mathrm{u}(\mathrm{t}), \mathrm{t} = 1, 2, \dots \tag{1}$$

where L is the lag-operator such that $L^k x(t) = x(t-k)$; d is a real positive number, and u(t) is a well-behaved process with mean zero and constant variance and that may include serial correlation as in the stationary ARMA processes. Note that if d = 1, we have unit roots, and if u(t) is ARMA(p, q), x(t) follows then an ARIMA(p, 1, q). The polynomial in L on the left-hand side of (1) can be expanded in terms of its Binomial representation such that, for any real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \dots \tag{2}$$

and thus equation (1) becomes:

$$x_t = dx_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \dots + u_t \tag{3}$$

According to this equation (3), if the differencing parameter d is an integer, x_t depends only on a finite number of previous observations; however, if it is a fractional value, the series will depend on its entire past history. Thus, the natural generalization of this to any real value d, is the fractional ARIMA (ARFIMA) of orders p, d, and q, for the AR, the differencing factor and the MA process respectively. (See Granger, 1980, 1981; Granger and Joyeux, 1980; Hosking, 1981; for the representation of these models). For the empirical application, we also suppose initially that x(t) in (1) are the errors in a regression model that incorporates an intercept and a linear time trend,

$$\mathrm{y}(\mathrm{t}) = \alpha + \beta\, \mathrm{t} + \mathrm{x}(\mathrm{t}), \mathrm{t} = 1, 2, \dots \tag{4}$$

where α and β are also unknown parameters to be estimated along with d. This model specification based on (1) and (2) clearly outperforms other classical approaches like the trend stationarity (if d = 0) and all the unit root approaches (if d = 1), allowing for a higher degree of flexibility in the dynamic specification of the models. Furthermore, the higher the differencing parameter d is, the higher the association is between the observations and d can be taken as a measure of the degree of persistence (dependence) in the data. In this context, if d is smaller than 0.5, the time series is covariance stationary; however, $d \geq 0.5$ indicates lack of it and persistence properties. In addition, d values below 1 support the hypothesis of mean reversion with shocks having transitory effects, decaying hyperbolically slowly to zero. On the other hand, if $d \geq 1$, there is lack of this property implying permanency of shocks. The application of a fractional integration framework provides a higher degree of flexibility in the dynamic specification of the series and avoids false unit roots results in cases when d is close to 1 (Diebold and Rudebush, 1991; Hassler and Wolters, 1994; Caporale and Gil-Alana, 2014; etc.).

In this paper we estimate the differencing parameter d using a very simple version of the method developed by Robinson (1994) and widely used in empirical applications of fractional integration (see Gil-Alana and Robinson, 1997 for its implementation). It is essentially a Lagrange Multiplier (LM) test that uses a frequency domain version of the likelihood function. This approach has numerous advantages over others. First, it is based on testing the null hypothesis H_o: $d = d_o$ in (3) for any real value d_o, including those outside the stationarity region ($d_o \geq 0.5$); thus, the confidence bands include all non-rejection values of the differencing parameter independently of its stationary or nonstationary nature; second, it has a standard N(0,1) asymptotic distribution, and this behavior holds whether or not deterministic terms are included in the model; third, it also allows for weak autocorrelation in the error term; fourth, it is the most efficient method in the Pitman sense against local departures from the null.

4. Discussion of results

Starting with the original data (in Tables 4 and 5), bioenergetic results are similar in the three series, with values slightly above 0.80 and the I(1) null cannot be rejected in any of the three series. For residential and all data, a time trend is significantly positive, while it is insignificant for manufacturing. For fossil data, once more the unit root null cannot be rejected in any single case, the values of d ranging from 0.72 (Manufacturing) to 1.03 (Electricity and Heat). The time trend is positive for manufacturing, residential and road transport. Therefore, both biogenic and fossil emission time series are not expected to have mean reversion properties at the 95 % level of significance, and further

Table 3
Descriptive statistics of selected data

	Biogenic			Fossil						
	Manufacturing	Residential	Gas	Manufacturing	Residential	Electricity and Heat	Civil airline	Railways	Road transport	Petroleum
Mean	196,238	59,188	59,152	604,563	648,839	1,910,601	162,667	35,417	1,252,058	260,967
Median	203,260	76,840	50,586	517,639	624,990	1,893,664	165,474	33,521	1,288,241	256,056
Maximum	267,703	105,481	133,311	1,104,109	877,788	2,560,424	203,803	45,897	1,544,553	348,290
Minimum	98,413	21,113	5530	407,538	506,639	1,082,100	112,043	25,162	813,900	220,081
Std. Dev	43,597	32,540	49,027	176,267	93,408	429,003	21,783	5466	208,167	25,939
Std. Dev/Mean	0.222	0.550	0.829	0.292	0.144	0.225	0.134	0.154	0.17	0.10
Skewness	−0.979	−0.102	0.198	0.902	1.208	−0.027	−0.115	0.439	−0.278	1.100
Kurtosis	3.094	1.217	1.322	2.711	3.370	1.835	1.903	2.126	1.7704	4.737735
Jarque-Bera	8.492	7.113	3.717	7.376	13.189	3.003	2.773	3.386	4.019	17.364
Probability	1.4 %	2.9 %	15.6 %	2.5 %	0.1 %	22.3 %	25.0 %	18.4 %	13.4 %	0.0 %
Observations	53	53	30	53	53	53	53	53	53	53

Table 4
Estimates of d. Original data

Series	No terms	An intercept	An intercept with a time trend
CO_2 biological			
Manufacturing	0.93 (0.76, 1.19)	**0.81 (0.61, 1.12)**	0.81 (0.61, 1.13)
Residential	0.82 (0.61, 1.14)	0.84 (0.67, 1.14)	**0.83 (0.60, 1.14)**
Gas	**1.37 (1.17, 1.57)**	1.26 (1.06, 1.47)	1.24 (0.98, 1.50)
All biological	0.93 (0.78, 1.17)	0.84 (0.73, 1.03)	**0.83 (0.69, 1.03)**
CO_2 fossils			
Manufacturing	0.82 (0.67, 1.04)	0.82 (0.67, 1.04)	**0.72 (0.53, 1.03)**
Residential	0.97 (0.78, 1.24)	0.97 (0.78, 1.24)	**0.86 (0.67, 1.19)**
Electricity and Heat	1.03 (0.87, 1.26)	**1.03 (0.87, 1.26)**	1.15 (1.04, 1.31)
Civil airline	0.96 (0.75, 1.29)	**0.96 (0.75, 1.29)**	0.75 (0.59, 0.99)
Railways	0.94 (0.77, 1.19)	**0.99 (0.57, 1.15)**	0.78 (0.57, 1.15)
Road transport	0.99 (0.80, 1.27)	0.96 (0.75, 1.25)	**0.98 (0.81, 1.22)**
Petroleum	0.97 (0.79, 1.23)	**0.88 (0.66, 1.22)**	0.88 (0.67, 1.22)
All fossils	0.93 (0.74, 1.19)	**0.94 (0.80, 1.17)**	0.94 (0.80, 1.16)

The values in parenthesis indicate the 95 % confidence bands; those in bold indicate the selected specification for each series.

Table 5
Estimated values obtained with the selected models. Original data.

Series	d (95 % interval)	Intercept (tvalue)	Time trend (tvalue)
CO_2 Biological			
Manufacturing	0.81 (0.61, 1.12)	201692.46 (7.58)	–
Residential	0.83 (0.60, 1.14)	18660.62 (1.80)	1588.24 (1.99)
Gas	1.37 (1.17, 1.57)	–	–
All biological	0.83 (0.69, 1.03)	253104.00 (11.35)	7261.22 (4.21)
CO_2 fossils			
Manufacturing	0.72 (0.53, 1.03)	1047879.22 (22.40)	−11717.65 (−4.48)
Residential	0.86 (0.67, 1.19)	856087.43 (27.62)	−53245.87 (−2.02)
Electricity and Heat	1.03 (0.87, 1.26)	1064327.41 (12.93)	–
Civil airline	0.96 (0.75, 1.29)	136295.36 (12.12)	–
Railways	0.99 (0.57, 1.15)	39287.22 (12.59)	–
Road transport	0.98 (0.81, 1.22)	803456.93 (18.49)	11834.93
Petroleum	0.88 (0.66, 1.22)	294632.53 (20.76)	–
All fossils	0.94 (0.80, 1.17)	4459371.50 (26.70)	–

external policies need to be taken to correct current levels.

In the case of the manufacturing sector, this lack of mean reversion reflects its carbon-intensive nature, although it has achieved an accumulative 45 % reduction in emissions since 1970. This decline is attributed to advances in energy efficiency and cleaner technologies, as well as in the relocation of activities to countries with laxer environmental regulations, such as China and India (Wang et al., 2022). Such results are in line with the US industry-specific studies of Charles et al. (2024) and Durga et al. (2024), that focused on the pulp and paper, and iron and steel industries, respectively, and expect achieving net-zero US CO2 emissions by 2050. Similarly, in Electricity and Heat Production we also found negative trends since year 2000 (−36 %), that are in line with Jeon (2022), that examined the relationship between CO_2 emissions and renewable energy, noting that today most of the US new installed electricity capacity is based on renewables (Bird et al., 2025). Therefore, persistency suggests that this current profile will continue in the future.

With logged data (Tables 6 and 7), some values differ from the unlogged ones. Log transforms multiplicative models to additive models and therefore is used to reduce the skewness (West, 2022). Starting with the biological ones (in the upper tables), the time trend is statistically significantly positive for all, while it is insignificant for manufacturing and residential. For the latter two, the estimates of the differencing parameter d are 0.84 and 0.98 and the unit root cannot be rejected. Specifically, in the residential sector, after year 2000 there has been a 21 % decrease in emissions due to the adoption of more efficient heating systems, energy-efficient appliances and the increased use of renewable energy sources in homes. Programs such as “Energy Star” have been decisive in this transition, although there are still inequalities in their implementation due to differences in state policies and economic accessibility (Pistochini et al., 2022).

However, in all cases, the estimate of d is 0.76, and the unit root null is now rejected in favor of mean reversion. Therefore, application of logs would help in the analysis and predictability of bioenergetic emissions. However, with fossils, as with the original series, the time trend is found to be positive for manufacturing, residential and road transport, but unlike that case, slow mean reversion occurs now for Manufacturing ($d = 0.67$) and for Civil Airline (0.76). In these two cases, the adoption of more efficient systems would suggest the change of this pattern between original and logged data as slow mean reversion patterns would be also expected ($0.5 < d < 1$). The Road Transport sector has seen a cumulative 89 % increase in emissions since 1970, driven by reliance on the private car and growing demand for SUVs, which in 2023 accounted for 48 % of global car sales (EIA, 2024). Although hybrid and electric technologies have advanced significantly, the positive impact of these innovations has been offset by a preference for larger, less efficient vehicles.

Table 6
Estimates of d. Logged data

Series	No terms	An intercept	An intercept with a time trend
CO_2 biological			
Manufacturing	0.94 (0.76, 1.19)	**0.84 (0.65, 1.15)**	0.84 (0.65, 1.15)
Residential	0.92 (0.74, 1.18)	**0.98 (0.78, 1.31)**	0.98 (0.75, 1.31)
Gas	**1.34 (1.13, 1.56)**	1.23 (1.01, 1.44)	1.22 (0.98, 1.46)
All biological	0.93 (0.76, 1.19)	0.78 (0.66, 0.99)	**0.76 (0.60, 0.99)**
CO_2 fossils			
Manufacturing	0.93 (0.75, 1.19)	0.66 (0.57, 0.91)	**0.67 (0.50, 0.94)**
Residential	0.94 (0.76, 1.18)	0.77 (0.60, 1.11)	**0.78 (0.60, 1.10)**
Electricity and Heat	0.93 (0.76, 1.19)	**1.18 (1.05, 1.37)**	1.16 (1.05, 1.33)
Civil airline	0.94 (0.76, 1.20)	**0.67 (0.52, 0.94)**	0.68 (0.54, 0.94)
Railways	0.94 (0.77, 1.19)	**0.76 (0.55, 1.13)**	0.76 (0.55, 1.13)
Road transport	0.94 (0.76, 1.19)	1.03 (0.74, 1.34)	**1.03 (0.85, 1.30)**
Petroleum	0.93 (0.76, 1.19)	**0.90 (0.69, 1.22)**	0.89 (0.69, 1.22)
All fossils	0.93 (0.76, 1.18)	**0.92 (0.77, 1.15)**	0.92 (0.77, 1.15)

The values in parenthesis indicate the 95 % confidence bands; those in bold indicate the selected specification for each series.

Table 7
Estimated values obtained with the selected models. Logged data

Series	d (95 % interval)	Intercept (tvalue)	Time trend (tvalue)
CO_2 biological			
Manufacturing	0.84 (0.65, 1.15)	12.210 (78.43)	–
Residential	0.98 (0.78, 1.31)	9.959 (58.65)	–
Gas	**1.34 (1.13, 1.56)**	–	–
All biological	0.76 (0.60, 0.99)^{MR}	12.529 (237.71)	0.0169 (5.18)
CO_2 fossils			
Manufacturing	0.67 (0.50, 0.94) ^{MR}	13.851 (221.77)	−0.0168 (−5.46)
Residential	0.78 (0.60, 1.10)	13.658 (287.48)	−0.0077 (−2.46)
Electricity and Heat	1.18 (1.05, 1.37)	13.879 (322.66)	–
Civil airline	0.67 (0.52, 0.94) ^{MR}	11.835 (166.56)	–
Railways	0.76 (0.55, 1.13)	10.576 (119.35)	–
Road transport	1.03 (0.85, 1.30)	13.605 (393.67)	0.0110 (2.08)
Petroleum	0.90 (0.69, 1.22)	12.593 (244.73)	–
All fossils	0.92 (0.77, 1.15)	15.3108 (443.85)	

EPA-driven multi-pollutant emissions standards are an important step toward reducing emissions in this sector, but ensuring sustained reductions will require complementary policies, such as incentives for electric vehicle adoption and the expansion of charging infrastructure. (EPA, 2024c; EIA, 2024).

In any case, for both types of emissions the empirical results indicate values of d very close to 1 with a 95 % confidence interval close to 1.2. Thus, the expected response to external shocks would be a slow mean reverting processes with a large probability; or a permanent one with a minor but significant probability. Similar results were obtained when using alternative approaches such as the parametric maximum likelihood approach of Sowell (1992) or the semiparametric Whittle approach of Robinson (1995). This empirical result is in line with all previous studies that mention long-term persistence in CO_2 emissions (Gil-Alana et al., 2017; Gil-Alana and Trani, 2019; Tiwari et al., 2021; Erdogan et al., 2022 or Pata and Aydin, 2023 among others). Thus, as the long-term trend is still positive (13 % growth in the 1970–2022 period), we believe that stronger policies must be applied to make further reductions. Even though emissions, in general terms, have been reduced after year 2000 (when the total amount of these emissions peaked) some recent studies as Lamb et al. (2021) note that the recent evolution in the 2010–2018 period has been almost flat in the US. Furthermore, we have verified in our previous results that not all sectors are behaving in the same way. For instance, Manufacturing and Residential sectors, have been showing clear decreasing patterns since 1970 (−45 % and −21 % respectively), and therefore this persistent profile would suggest that their associated emissions are expected to be smaller in the future if the current adopted policies were maintained. Main reasons that explain this pattern might be improvements in energy efficiency, processing and manufacturing (Wang et al., 2019). We question whether the current rate of reduction is enough to achieve carbon neutrality by 2050 as agreed by the IPCC, considering that the logged data shows evidence of mean reversion for manufacturing sectors.

Specific policies for the manufacturing sector to maintain this CO_2 reduction pattern should include industry-specific energy efficiency standards with regular updates, financial support for industrial carbon capture and utilization technologies, tax incentives for green manufacturing processes, and border carbon adjustments to prevent emissions leakage (Gillingham and Stock, 2018). In the Residential and Commercial Buildings sector, the implementation of stringent national building energy codes, expanded rebate programs for energy-efficient appliances and heating systems, financial incentives for deep building retrofits, and policies promoting building electrification would be most effective (Nadel and Ungar, 2019). These sector-specific approaches, when implemented cohesively, would address the persistent emission patterns identified in this research and might help the United States meet its climate commitments while driving innovation and economic growth in low-carbon industries (Bistline and Young, 2019; Carley and Konisky, 2020).

However, following Table 1, the two major sector emission contributors today (60.5 %) are Electricity and Heat, and Transportation. In the case of Electricity and Heat, after a strong growth between 1970 and 2000 (141 %), the trend becomes negative only after year 2000 (−35 %). Some authors point that the growth pattern in CO_2 emissions from energy systems is directly associated with the rising GDP per capita profile because of the direct relationships between energy, electricity demand, and economic growth (Khanna and Rao, 2009; Stern, 2011). This initial growth is linked to the intensive use of coal in the 1970s and 1980s, when it was the predominant source of electricity generation. However, the reduction in emissions since 2000 (−35 %) reflects a significant shift to natural gas, which emits less CO_2 per unit of energy generated, and a growing adoption of renewable sources such as wind and solar, driven by federal and state tax incentives. States such as Texas and California have led this transition due to specific policies supporting clean energy and the modernization of transmission infrastructure (EIA, 2021).

However, in the US profile we see additional factors that might have pushed towards these reductions after year 2000. First, a widespread coal to gas switch driven by low gas prices, the shale gas boom, and federal tax credit incentives (Peters et al., 2017, 2020), and second, the increase in renewable capacity expanding rapidly in Texas, California and across the Midwest (Mohlin et al., 2019). In fact, today renewable energies outpaced other generation sources and collectively accounted for around 90 % of the US' new installed capacity in 2024 (U.S. Energy Information Administration, 2025). In 2024, all carbon free electricity sources, including nuclear, supplied nearly 44 % of electricity, while renewables, including small-scale solar, supplied nearly 25 %. (Bird et al., 2025). Therefore, for the Electricity and Heat Generation sector, policies should focus on accelerating the transition to renewable energy through enhanced tax incentives, implementing stronger renewable portfolio standards with specific technology carve-outs, and developing a comprehensive national strategy for grid modernization to accommodate higher renewable penetration (Gillingham and Stock, 2018; Carley and Konisky, 2020).

In the case of Road Transportation, the growth pattern remains positive (89 % total growth and only 7 % after year 2000). Similarly with Heat and Energy, literature points to a direct relationship with GDP per capita, as transport facilitates the movement of people and goods, essential services and social interactions (Schafer et al., 2009; Gota et al., 2019). However, other authors point out the culture impact of the private car. As in the US this mostly dominates passenger travel activity (81 % share, EC, 2019) the increasing adoption of larger and heavier vehicles (sports utility vehicles or SUVs), had maintained the carbon intensity of the transport sector. Globally, SUVs accounting for 48 % of global car sales in 2023 were responsible for over 20 % of the growth in global energy-related CO_2 emissions last year (IEA, 2024b). Therefore, new efficiency gains of incoming hybrid and electric vehicles are still uncompensated with this trend towards larger and heavier cars (Lamb et al., 2021).

In order to assess the incoming impact of these two CO_2 largest emission sectors, we have built two ARIMA models* to project the existing time series in the 5-year future, finding confirmation of both the negative trend followed by Electricity and Heat, and a positive trend for Road and Transportation. Therefore, we believe that stronger policies need to be aimed at the Road and Transportation sectors. This includes implementing stricter emissions standards for light and heavy-duty vehicles, along with more aggressive financial incentives for the purchase of electric vehicles, such as those adopted in Norway, where electric cars accounted for 65 % of total sales in 2022 (EIA, 2024). Some additional measures might include stricter fuel economy standards for both light and heavy-duty vehicles, expanded fiscal incentives for electric vehicle purchases with particular emphasis on middle and lower-income consumers, substantial investment in nationwide charging infrastructure, and dedicated funding for public transportation systems in urban areas (Chen et al., 2021).

In this context, some recent measures were approved in the trucking sector such as the Multi-Pollutant Emission Standards for light- and medium-duty vehicles from 2027 (EPA, 2024c), GHG Emission Standards for heavy-duty vehicles (EPA, 2024c) or National Zero-Emission Freight Corridor Strategy to electrify heavy-duty vehicle fleets (US Department of Transportation, 2024) in line with those adopted in the EU. We believe that these final EPA standards are critical to reduce CO_2 emissions and in fact, they are expected to reduce them by approximately one billion metric tons by 2027 and generate climate benefits worth $13 billion per year (EPA, 2024c). Additional measures such as the increase of opportunities to recharge electric vehicles, or improving fuel vehicles with alternative fuels (EC, 2008) would complement the aforementioned ones to change both short- and long-term patterns.

To evaluate dependencies between sectors in the overall emissions, we have also built a correlation matrix between total emissions and their components. In the case of fossil emissions (Table 8a) results confirms large dependencies between Total Emissions and Heat and Electricity (0.93) and with Road and Transport (0.77). Furthermore, there is a clear additional relationship between Heat and Road (0.83). As noted before, the reason for these strong correlations appears to be the historical relationship between these sectors with GDP and the economic cycle (Khanna and Rao, 2009; Schafer et al., 2009; Stern, 2011; Gota et al., 2019; etc.). In the case of Heat and Electricity, the high assessment with total emissions reflects its predominant role as the largest emitter in previous decades. The transition from coal to natural gas and, more recently, to renewables has reduced carbon intensity, but reliance on electricity remains critical for other sectors, such as Manufacturing and Residential, which rely indirectly on clean energy sources to reduce their emissions (EIA, 2021).

Therefore, as Heat and Electricity emissions have fallen in recent times, a major effort in the reduction of Road and Transportation emissions should have a significant impact in the reduction of the total US emissions. Road Transport, however, presents a unique challenge. Although its estimated share of total emissions is lower than that of the Electricity and Heat sector, its continued growth in emissions since 1970 and the slow adoption of clean technologies, such as electric vehicles, have prevented a significant change in the overall trend in the sector (Lamb et al., 2021). Implementation of policies such as heavy fleet charging corridors and multi-pollutant emissions standards could accelerate this transition but will require additional investments in charging infrastructure and subsidies (EPA, 2024c; U.S. Department of Transportation, 2024).

Some authors point that urban electrification has notably progressed in recent times, especially in scooters, buses and other different micromobility urban freight modes (Taiebat and Xu, 2019). However, this urban electrification has been uneven and limited mainly to metropolitan areas with supportive policies. In suburban and rural regions, where the private automobile is the main mode of transportation, emissions remain high due to the predominant use of large and heavy vehicles. This cultural preference, combined with low fossil fuel prices, has slowed down the adoption of cleaner technologies (EIA, 2024).

Conversely, as electrification of road transport holds much promise, more stringent policies to reduce car dependence would be desirable, such as demand management policies (Creutzig et al., 2018; Mattioli et al., 2020; Milovanoff et al., 2020) or new fashion trends towards lighter and more efficient cars (EIA, 2024).

With regards to other sectors, negative correlation is observed in some cases, especially for Manufacturing (−0.53) and Residential (−0.31) due to their important weight in total emissions, as both sectors were experiencing negative trends with positive total emission growths. In the Manufacturing sector, negative offsetting reflects the success of strategies such as the relocation of carbon-intensive activities to countries with lower costs and fewer environmental restrictions, a phenomenon known as carbon leakage. While this has reduced national emissions, it has increased global emissions in regions with less stringent environmental policies (Wang et al., 2019). In the Residential sector, energy improvements, such as the use of more efficient appliances and thermal insulation systems, have contributed significantly to emissions reductions, but regional disparities and unequal access to retrofit programs limit the potential for reductions at the national level (Pistochini et al., 2022).

In the case bioenergy sectors (Table 8b) these components were clearly positive but their weight over total emissions is still limited (below 0.7). However, it should be important in further works to analyze in more detail the gas correlation (0.98) due to the important weight that gas has in bioenergy emissions versus their total gas emissions (89 % in 2022). The reliance on natural gas in the bioenergy and power generation sectors underscores the need to diversify renewable energy sources and increase investment in carbon capture and storage technologies (EIA, 2024).

As a final exercise we check the hypothesis of a major long-term pattern change due to recent environmental policies. We have studied major structural breaks (Bai and Perron, 2003) and estimated the value of the integration factor d in the most recent sub-series (Table 9). In the case of Fossil Fuels, significant structural breaks after year 2000 belong only to Electricity Generation and Civil Airlines (around 2007) and Road Transportation (2016). In the case of Electricity Generation, policies such as tax incentives for renewables and stricter emissions standards (EPA, 2016) have played a key role in driving the shift from coal to gas, although this process is not rapid. For trucking, policies vary significantly by administration: while the Obama administration implemented stricter efficiency standards in 2009, the Trump administration relaxed these regulations in 2016, negatively impacting the trajectory toward

Table 8b
Correlation table for bioenergy sectors under analysis

	All	Gas	Residential	Manufacturing
All	1.00	0.98	0.56	0.67
Gas	0.98	1.00	0.47	0.66
Residential	0.56	0.47	1.00	0.11
Manufacturing	0.67	0.66	0.11	1.00

Table 8a
Correlation table for fossil sectors under analysis

	All	Civil Airline	Electricity and Heat	Manufacturing	Petroleum	Railway	Residential	Road and transportation
All	1.00	0.65	0.93	−0.53	0.14	−0.36	−0.31	0.77
Civil Airline	0.65	1.00	0.69	−0.46	−0.18	−0.47	−0.41	0.50
Electricity and Heat	0.93	0.69	1.00	−0.74	−0.17	−0.60	−0.59	0.83
Manufacturing	−0.53	−0.46	−0.74	1.00	0.43	0.60	0.86	−0.88
Petroleum	0.14	−0.18	−0.17	0.43	1.00	0.46	0.72	−0.19
Railway	−0.36	−0.47	−0.60	0.60	0.46	1.00	0.61	−0.40
Residential	−0.31	−0.41	−0.59	0.86	0.72	0.61	1.00	−0.70
Road and transportation	0.77	0.50	0.83	−0.88	−0.19	−0.40	−0.70	1.00

Table 9
Estimated structural breaks following and d value of the ending subseries

Series	No terms	Breaks	d ending subseries
CO_2 biological			
Manufacturing	0.81 (0.61, 1.12)	1990	0.71
Residential	0.83 (0.60, 1.14)	1992	0.80
All biological	0.83 (0.69, 1.03)	None	0.83
CO_2 fossils			
Manufacturing	0.72 (0.53, 1.03)	none	0.72
Residential	0.86 (0.67, 1.19)	1981	0.57
Electricity and Heat	1.03 (0.87, 1.26)	2006	0.47
Civil airline	0.96 (0.75, 1.29)	2008	−0.04
Railways	0.99 (0.57, 1.15)	none	0.99
Road transport	0.98 (0.81, 1.22)	2016	n/a
Petroleum	0.88 (0.66, 1.22)	1980	0.84
All fossils	0.94 (0.80, 1.17)	none	0.94

less reliance on fossil fuels (Plumer and Popovich, 2018).

Regarding the Heat and Electricity shock, due to the relationship between these components and the GDP (Khanna and Rao, 2009; Stern, 2011); and the great impact of the 2007 financial crisis we believe that this shock is associated with economic reasons more than specific policies applied after year 2000. In particular, the coal to gas switch driven by low gas prices is not a fast process and the increase in renewable capacity is a process developed in a later decade. Similarly, we believe that economic reasons arising from to the oil crisis of 1979 were the cause of the Petroleum (1980) and Residential (1981) shocks. However, in the specific case of the Road and Transportation shock (2016), we were not able to estimate the d-value due to the very reduced number of ending samples after this shock. With the positive trend seen in the ARIMA model projections (Fig. 2) and the absence of significant economic events, we believe that this shock is policy related but not in the right direction to reduce emissions. As under the Obama administration (2009), stricter emission standards were established in the transportation sector, reducing fuel consumption to an average of 54 gallons per mile by 2025 (The White House, 2009; EPA, 2009); with the election of President Trump in 2016, these principles were significantly relaxed, and no specific policies were applied (Plumer and Popovich, 2018).

Finally, in the case of bioenergetic emissions, we found evidence of no major structural breaks after year 1992 and therefore new policies after year 2000 should have no major impact in the long-term trend. Specifically, in 1990 inflation reached 6.1 %, the highest rate since 1981, which might suggest that these Residential and Manufacturing breaks could have been affected by a fall in demand. Consequently, we believe that future work should focus on comparing these critical US sectors with those of other countries to evaluate the success of the implemented policies, especially in the Road and Transport sector seeking some stricter policies on the part the US to be able to meet IPCC agreements.

5. Discussion and concluding comments

In this paper we have examined the long-term US CO_2 emission persistence for the IPCC standard sectors for both fossil and bioenergetic components. For this purpose, we have analyzed emissions for the time period that goes from 1970 to 2022 with yearly samples following the EDGAR database (Crippa et al., 2023). Similarly to other previous studies (Gil-Alana et al., 2017; Gil-Alana and Trani, 2019; Tiwari et al., 2021; Erdogan et al., 2022 or Pata and Aydin, 2023 among others), the unit root null cannot be rejected in any single case, for both fossil and bioenergetic contributors. Most of the results lie within the interval (0.5 $< d <$ 1), time series supporting the hypothesis of slow mean reversion with shocks having transitory effects, decaying hyperbolically slowly to zero. However, as in the 95 % confidence interval the unit root null hypothesis cannot be rejected, or is rejected in favor of $d > 1$, there is a significant probability of shocks being persistent with no mean reverting properties. Thus, due to this persistent nature of the emissions series, there is a clear need to introduce further policies to change the long-term pattern and ensure a correction in the current levels.

A deeper analysis of the IPCC standard sectors reveals new insights for the global community. Specifically, sectors such as Manufacturing, Residential, and Heat/Electricity have shown decreasing emission patterns since 2000. This persistent trend suggests that emissions from these sectors are likely to continue decreasing in the future with the current emission policies. However, Road and Transportation sectors, which have maintained a positive slope in emissions, indicate a probable increase in future emissions without additional measures. Given that Road and Transportation account for 29 % of total emissions, it is crucial to implement further policies to meet future IPCC commitments.

Furthermore, we have analyzed one-to-one sector relationships with a correlation matrix and the structural breaks of the IPCC sector contributors. We find evidence of an important long-term relationship between fossil emissions and Heat/Electricity (0.93) and Road and Transport (0.77), raising the idea that policies in these two sectors would generate a significant reduction in the volume of total emissions. On the other hand, empirical results of structural breaks suggest that these are mostly related to economic shocks than to environmental policies. In fact, when analysing the existence of breaks, it can be observed that they match with economic events, except for the case of

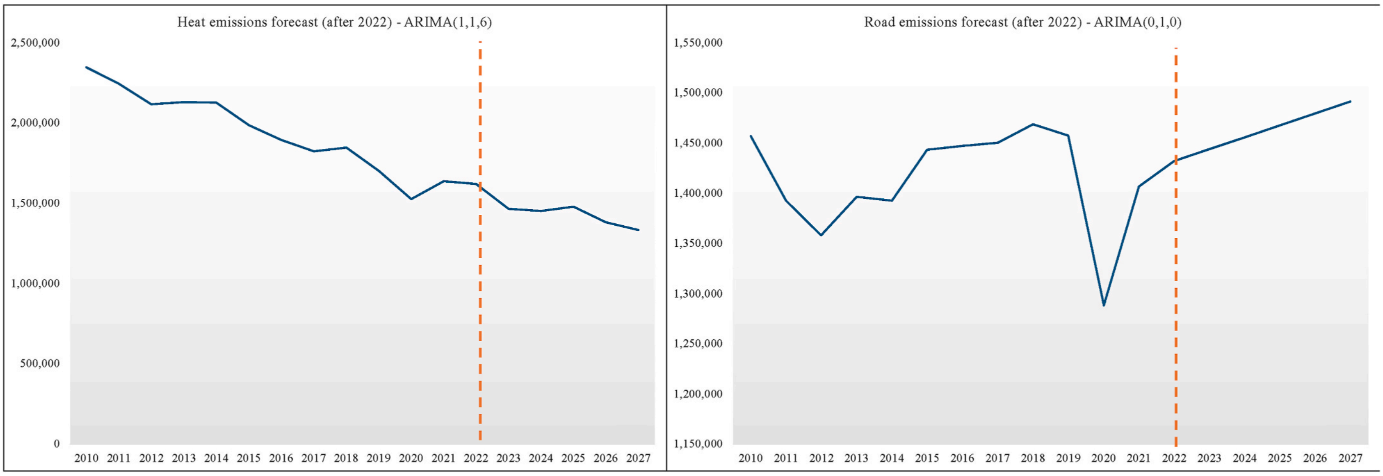

Fig. 2. ARIMA 5yr projections of fossil heat and road emissions (2022–2027).
* As the estimated d-values for these sectors were 1.03 and 0.98, we decided to round these values to 1 forecast with simple ARIMA (p,1,q). For these cases, best fitting models were ARIMA(1,1,6) for heat and electricity and ARIMA (0,1,0) for road and transportation.

Road and Transport (2016). Specifically, in 1990, the inflation crisis for the Residential and Manufacturing sectors, the oil crisis for the breakdown of Petroleum (1980) and Residential (1981), or the 2007 economic crisis for Electricity and Heat Generation and Civil Airlines. Future works should focus on the comparison of the results of these critical sectors with those from other parts of the world to evaluate the success of the adopted emission policies. In addition to these structural breaks, other alternative approaches, based for example on non-linear trends could be taken into account. In doing so, we could avoid the abrupt changes produced by the breaks, being consistent with the literature that related nonlinear models with fractional integration (e.g., Diebold and Inoue 2001; Granger and Hyung, 2004; etc.). Examples of these approaches are the Chebyshev polynomials in time (Cuestas and Gil-Alana, 2016), the Fourier functions in time (Gil-Alana and Yaya, 2021) and the use of neural networks (Yaya et al., 2021) within the I(d) frameworks.

We believe that stronger specific environmental measures should be taken to change the long-term pattern, specifically in the Road and Transportation sector, as this is the unique sector that maintains a positive trend. Some suggested measures might be similar to those implemented in the EU, which has successfully reduced emissions through a combination of policies such as the Emissions Trading System (ETS), investments in renewable energies and energy efficiency improvements (EC, 2008). Implementing similar strategies in the US could help achieve significant reductions in emissions and meet future IPCC commitments. However, as the electrification of this sector holds much promise, more stringent policies in the short term to reduce car dependence would be desirable as well as new designs towards lighter and more efficient cars.

Regarding other sectors, we observe negative correlation in some cases. Here, Manufacturing (−0.53) and Residential (−0.31) are especially important due to their important weight in overall emission trends despite experiencing positive growth in total emissions. These sectors, showing persistent decreasing patterns since 2000, indicate potential for continued reductions. In general lines, policies should focus on accelerating the transition to renewable energy through enhanced tax incentives with stronger renewable portfolio standards; and include industry-specific energy efficiency standards with more stringent national building energy codes. Finally, bioenergy sectors display a positive correlation with total emissions, though their contribution remains limited. The high correlation of gas emissions (0.98) within bioenergy sectors, representing 89 % of total gas emissions in 2022, underscores the need for a detailed analysis and strategic interventions in this area.

CRediT authorship contribution statement

Miguel A. Martin-Valmayor: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Formal analysis, Data curation, Conceptualization. **Juan Infante:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis. **Nieves Carmona-González:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis. **Luis A. Gil-Alana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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