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ATMOSPHERIC POLLUTION IN 10 US CITIES: TRENDS AND PERSISTENCE

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Abstract

This paper analyses trends and persistence in atmospheric pollution in ten US cities over the period from January 2014 to January 2024 using fractional integration methods. The results support the hypothesis of long memory and mean reversion in atmospheric pollution in all cities examined. They also indicate that Boston is the only city in the sample where atmospheric pollution exhibits a significant positive linear trend, though it is also characterised by the lowest degree of integration, which implies that shocks have transitory effects and mean reversion occurs at a fast rate.

Keywords: Atmospheric pollution; particular matter ($PM_{2.5}$); fractional integration; long memory; persistence

JEL Classification: C22, Q53, Q58

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1. Introduction

According to the World Health Organization (WHO, 2021), exposure to air pollution causes seven million premature deaths worldwide each year. Among the most harmful pollutants is $PM_{2.5}$. The World Bank (2022) estimated that the cost of health damage due to air pollution is US$8.1 trillion per year, equivalent to 6.1% of global GDP, and that a 20% decrease in $PM_{2.5}$ would result in a 16% increase in the employment growth rate and a 33% increase in labour productivity. The IMF is also focusing on climate change by integrating it into its annual economic assessments and adding climate data to its set of key macroeconomic indicators (IMF, 2023). In addition, it is incorporating emission reduction targets into its macroeconomic policy discussions with high polluting countries and setting climate adaptation targets for vulnerable countries.

The European Commission Report (2023) on global greenhouse gas (GHG) emissions resulting from anthropogenic activities calculates that these have increased, on average, by almost 1.5% annually since 1990, and in 2022 were around 62% higher than in 1990. In the latter year, among the six major economies that were responsible for 61.6% of global GHG emissions (China, US, India, EU27, Russia and Brazil), four showed increases in those compared to the period before the onset of the Covid-19 pandemic in 2019 (China, +7.4%; India, +5.7%; Russia, +2.0%; Brazil, +2.3%), while two exhibited a decrease (US, –2.2% and EU27, –3.4%). The US is the second most polluting country in the world after China. These two nations alone produce almost half of all the carbon dioxide on the planet according to the Global Carbon Atlas (2022).

The issue of air pollution in the US was addressed by former US president Barack Obama in 2015 without success as the plan to reduce emissions of air pollutants was blocked before it came into force. However, on 16 August 2022, the Biden administration announced new regulations that the US would follow to reduce emissions of polluting gases, especially from existing power plants, as specified in the Inflation Reduction Act

(The White House, 2022), which was the most important piece of legislation on climate regulation in US history and reflected a growing concern about climate change.

As already mentioned, $PM_{2.5}$ represents a major health issue as it increases the risk of premature death and of various diseases (asthma, heart attacks, respiratory dysfunctions, etc.) and, moreover, it has harmful environmental effects such as haze, it affects ecosystems diversity, it contributes to acid rain, etc. (EPA, 2020). In 2002, it was estimated that, of the total emissions of six pollutants, $PM_{2.5}$ constituted only 6% of emissions, but accounted for 23% of the total gross annual gross human health damages. These damages amounted to 17 billion dollars (Muller and Mendelsohn, 2007). Sullivan et al. (2018) stressed the importance of analysing long-term data to acquire a better knowledge of $PM_{2.5}$ dynamics and formulate more effective environmental policies.

The present study contributes to this area of the literature by examining the evolution of $PM_{2.5}$ in ten US cities (Boston, Chicago, Dallas, El Paso, Los Angeles, New York, Phoenix, San Antonio, Seattle, and San José) over the period from January 2014 to January 2024 by means of a fractional integration framework. This approach is more informative than the standard one used in most air pollution studies, as it allows for both fractional and integer degrees of differentiation, and therefore it sheds light on the long-memory properties of the series, the possible presence of trends, mean reversion, persistence and the speed of adjustment towards the long-run equilibrium; it also provides information on whether the effects of shocks are transitory or permanent, which is a crucial piece of information for designing effective environmental policies.

The remainder of the paper is structured as follows: Section 2 briefly reviews the relevant literature; Section 3 outlines the methodology; Section 4 describes the data and presents the empirical results; Section 5 offers some concluding remarks.

2. Literature Review

The literature on air pollution and its effects on the health of the US population is extensive (Bevan et al., 2021; Malik et al., 2022; Remigio et al., 2022; Liu et al., 2023; etc.). Pokharel et al. (2023) note that around 1,300 deaths per year in the US, valued at about $13 billion, were due to primary $PM_{2.5}$ emissions from crop tillage. Other studies look at environmental inequality in the US and how the burden of air pollution exposure is not evenly distributed (Nadybal et al., 2020; Fong and Bell., 2021; Cook et al., 2021; Rubio et al., 2022; Bradley et al., 2024).

Some authors have studied the long-memory characteristics of air pollutants. Mei et al. (2023) use an air pollutant transport model based on complex networks to examine spatio-temporal variation of air pollution in several Chinese cities. Guan-Yu et al. (2022) emphasise the need for a spatio-temporal prediction model to analyse the chemical compositions of $PM_{2.5}$ and to assess exposure risks. They develop effective air pollutant reduction strategies, and, for this purpose, they use a hybrid deep learning/ Kriging model incorporating a meteorological normalisation technique. Gil Alana et al. (2020a) investigate air quality in the 50 US states by analysing the statistical properties of particulate matter (PM_{10} and $PM_{2.5}$) data sets; their results show the presence of significant negative time trend coefficients in several cases, implying that appropriate measures are being taken to improve the level of air quality. Bermejo-Muñoz et al. (2023) study the degree of persistence in $PM_{2.5}$ in 20 megacities using fractional integration techniques, and find mean reversion and only transitory effects of shocks. Caporale et al. (2021) analyse the statistical properties of PM_{10} in eight European capitals during 2014-2020 once more applying fractional integration methods, and conclude that all series are characterised by long memory and mean reversion.

Hadley et al (2017) identify residual fuel oil from marine traffic, biomass combustion emissions, seawater, and crustal materials as explanations for $PM_{2.5}$ in the northwestern United States. Their study uses a US EPA matrix factorisation model to analyse seasonal and long-term trends. Finally, Di et al. (2019) examine $PM_{2.5}$ concentration in the US between 2000 to 2015, and show that $PM_{2.5}$ predictions allow epidemiologists to obtain accurate estimates of the adverse health effects of $PM_{2.5.}$

3. Methodology

Environmental data such as those on air pollution are often thought to exhibit long memory, namely a high degree of dependence between observations even if they are very distant in time. This property can be modelled using a fractional integration framework. Specifically, a time series (say, x(t), t = 1, 2, …) is said to be fractionally integrated or integrated of order d, denoted as I(d), if it can be written in the following way:

$$(1 - B)^d \, x(t) = u\,(t), \quad t = 1, 2, \ldots, \tag{1}$$

where B is a backshift-operator, i.e., $B^s x(t) = x(t-s)$, and u(t) is a short-memory process, such as a white noise with zero mean and a constant variance.

The differencing parameter d can capture different types of stochastic behaviour such as:

1. Short memory, if d=0.
2. Long memory, if d>0, including:
   - 2a. Stationary processes, if $0 < d < 0.5$, and
   - 3a. Nonstationary process with mean reversion, if $0.5 \leq d < 1$
3. Unit roots if d=1
4. Explosive processes if d>1.

It should be noted that the fractional polynomial in (1) can be expanded as:

$$(1 - B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2 - \cdots$$

and thus the equality appearing in Equation (1) can be expressed as:

$$x_t = d x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t.$$

In this context, if d has a fractional value, x_t will be a function of all its past values, and therefore can be represented as an infinite AR process. These processes were introduced in the early 80s by Granger (1980), Granger and Joyeux (1980), Granger (1981) and Hosking (1981), and subsequently used in empirical papers. For instance, Gil-Alana and Robinson (1997) showed that the twelve US macroeconomic series examined in Nelson and Plosser (1982) in fact did not exhibit unit roots but were instead fractionally integrated, with an order of integration significantly below 1 implying mean reversion. Since then, such models have been estimated in many different fields, such as internet traffic and networking (Schennach, 2018), finance (Abbritti et al., 2016, 2023), tourism (Perez-Rodriguez et al., 2020; Gil-Alana and Payne, 2020), hydrology (Habib, 2020), climatology (Yuan et al., 2022), and environmental sciences (Gil-Alana et al., 2020a,b; Claudio-Quiroga and Gil-Alana, 2022, etc.).

For the empirical analysis we use a simple version of a testing method described in Robinson (1994) which has various advantages over other approaches; in particular, it is valid regardless of the order of integration, and it has a standard (normal) limit distribution. The functional form of this method is based on the Lagrange Multiplier (LM) principle (Gil-Alana and Robinson, 1997).

4. Data Description and Empirical Results

The data are taken from the World Air Quality Index (WAQI) website (https://aqicn.org/map/world/es/). Specifically, actionable information is obtained from air quality data using the US Environmental Protection Agency's (EPA) Nowcast algorithm that converts raw $PM_{2.5}$ readings into an air quality index value (ICA). The index is calculated using data for a period of 3 to 12 hours, depending on the particle concentration. The series provide information about the daily level of air quality based on the measurement of $PM_{2.5}$ in micrograms per cubic meter of air (μg/m$^{3)}$ over the period from January 2014 to January 2024 in ten US cities (Boston, Chicago, Dallas, El Paso, Los Angeles, New York, Phoenix, San Antonio, Seattle, and San Jose).

The original sources are Boston: https://www.mass.gov/topics/air-quality AirNow.gov; Chicago: http://www.epa.illinois.gov/; Dallas: Homepage-Texas Commission on Environmental Quality - www.tceq.texas.gov; El Paso: http://www.tceq.texas.gov/.; Los Angeles: AQMD-Home Homepage | California Air Resources Board; New York: https://dec.ny.gov/; Phoenix: https://www.maricopa.gov/AirNow.gov; San Antonio: Homepage-Texas Commission on Environmental Quality - www.tceq.texas.gov; San José: Homepage|California Air Resources Board; Seattle: http://www.ecy.wa.gov/. These ten cities have been chosen on the basis of two criteria: first, they are the most populated cities in the US according to the latest 2020 census, and second, data on $PM_{2.5}$ are available for the whole period under investigation.

Table 1 displays the estimated values of d in Equation (2), and their 95% confidence bands, for three different model specifications, namely without deterministic terms, with an intercept only, and with an intercept as well as a linear time trend. The general model is the following one:

$$y(t) = a + b\,t + x(t), \qquad (1 - B)^d\, x(t) = u(t), \quad t = 1, 2, \ldots, \qquad (2)$$

where y(t) is the observed variable of interest at time t; a and b are unknown parameters to be estimated, specifically a constant and the coefficient on a linear time trend; x(t) are the residuals from a linear regression model; d is the order of integration and measures the degree of persistence in the data; u(t) is the error term which is assumed to be a white noise process.

The estimates reported in the second column of Table 1 are those obtained when a = b = 0 in equation (2), i.e., when no deterministic terms are included; by contrast, those in column 3 correspond to the case when b = 0 and therefore only an intercept is included; finally those in column 4 are the ones for the specification with both parameters, a and b, freely estimated from the data, i.e. including both a constant and a linear time trend in the model. To select the best specification a general to specific approach is followed, i.e. the most general model including both the intercept and the time trend is estimated first, and is chosen if both coefficients are statistically significant; if the time trend is found to be insignificant, the model with a constant only is estimated next and this specification is chosen if this coefficient is significant; if it is not, the model without deterministic terms is finally selected. The estimates from the preferred model are shown in bold in Table 1. The upper half shows the results for the original series, while the lower one those for the logged series.

TABLE 1 ABOUT HERE

The results for the deterministic terms (not reported to save space, but available upon request) are very similar for the original and logged values. Boston is the only city where a linear time trend is found to be statistically significant, the estimated coefficient being 0.0054 for the original data, and 0.0001 for the logged series. Regarding the degree of persistence, which is measured by d, all the estimated values are in the interval (0, 1), which supports the hypothesis of long memory (d > 0) and mean-reverting (d < 1) behaviour. In the case of the original data, the highest degree of persistence is found for San Jose (with an estimated value of d of 0.71), followed by Seattle (0.67), Los Angeles (0.59) and Vancouver (0.59), all on the West Coast; by contrast, the lowest estimates of d are those for Chicago (0.44) and Boston (0.42). Similar results are obtained when using the logged series, all estimates being in the interval (0, 1), though being slightly lower than in the previous case, the highest coefficients being those for cities on the West Coast, namely Seattle and Los Angeles (d=0.57), while the lowest one is found in the case of Boston (d = 0.40), where in the event of a shock mean reversion occurs at the fastest rate.

To sum up, all the series analysed exhibit long memory and mean reversion. San Jose has the highest degree of persistence, followed by Seattle and Los Angeles, all these cities being on the West Coast, whilst the lowest estimates are obtained for Chicago and Boston. Interestingly, the latter city is also the only one with a positive linear trend in $PM_{2.5}$ pollution over the period under examination, with a possible negative impact on labour productivity, medical costs, quality of life and attractiveness of investments. However, its low degree of persistence suggests that the effects of shocks disappear faster than in the other cities, which is an important piece of information for the design of appropriate environmental policies. In fact, concern about pollution in Boston led to the adoption of a Climate Action Plan (2019) with 18 strategies focused mainly on the decrease of pollutants from buildings and transport, these being the main causes of pollution in the city.

5. Conclusions

In 2015, 9% of the American population lived in areas with $PM_{2.5}$ concentrations higher than the WHO recommendation of 10 μgm^{-3}, and 89% in areas with concentrations between 5 to 10 μgm^{-3}. Therefore analysing trends and persistence in $PM_{2.5}$ in the most populated US cities is essential to design better environmental policies. This paper sheds new light on these issues by applying fractional integration methods to data for 10 such US cities over the period from January 2014 to January 2024. The chosen framework is more general and flexible than standard models based on the standard I(0) versus I(1) dichotomy as it allows the differencing parameter to take any real value, including fractional ones; in this way crucial evidence about trends, persistence and mean reversion can be obtained, which can inform policy decisions.

In brief, long memory is detected in all cases, but different degrees of persistence are found in the 10 US cities considered; this implies that there is a greater need for decisive policy actions in cities, especially those on the West Coast, where the effects of shocks are more long-lived.

Our analysis can be extended in several ways. First, the pollutant examined here is $PM_{2.5}$, but the US Air Quality Index (AQI) which rates air conditions is based on the concentrations of five pollutants: tropospheric ozone, particulate matter (PM_{10} and $PM_{2.5}$), carbon monoxide, sulfuric dioxide and nitrogen dioxide; therefore it would be interesting to analyse the evolution of all these series to obtain more comprehensive evidence on trends and persistence in air pollutants. Further, the analysis could also be carried out for cities in other parts of the world. In terms of econometric modelling, the possible presence of structural breaks could be investigated by performing endogenous break tests to capture abrupt changes or by running rolling-window and recursive regressions for the case of gradually evolving parameters. Finally, possible cyclical patterns could be modelled, still in the context of long memory, by allowing for singularities in the spectrum at frequencies away from zero. Future work will focus on those issues.

References

Abbritti, M., Gil-Alana, L.A., Lovcha, Y., Moreno, A. (2016). Term structure persistence, Journal of Financial Econometrics 14, 2, 331-352.

Abbritti, M., Carcel, H., Gil-Alana L.A., Moreno, A. (2023). Term premium in a fractionally cointegrated yield curve, Journal of Banking and Finance 149, 106777. https://doi.org/10.1016/j.jbankfin.2023.106777

Bermejo-Muñoz, L., L.A. Gil-Alana, del Rio M. (2023), Time trends and persistence in PM2.5 in 20 megacities: evidence for the time period 2018–2020. Environmental Science and Pollution Research 30, 5603–5620. https://doi.org/10.1007/s11356-022-22512-z

Bradley, A.C., Croes, B.E., Harkins, C., McDonald, B.C., Gouw, J.A. (2024). Air Pollution Inequality in the Denver Metroplex and its Relationship to Historical Redlining. Environmental Science & Technology. https://doi.org/10.1021/acs.est.3c03230

Bevan, G.H., Freedman, D.A., Lee E.K., Rajagopalan, S., Al-Kindi, S.G. (2021). Association between environmental air pollution and county-level cardiovascular mortality in the United States by social deprivation index. American Heart Journal 235, 125-131, https://doi.org/10.1016/j.ahj.2021.02.005 .

Caporale, GM, Gil-Alana, LA, Carmona-González, N. (2021). Particulate matter 10 (PM $_{10)}$: persistence and trends in eight European capitals. Air Quality Atmosphere Health 14, 1097–1102. https://doi.org/10.1007/s11869-021-01002-0

Claudio-Quiroga, G., Gil-Alana, L.A. (2022). CO_2 emissions persistence: Evidence using fractional integration, Energy Strategy Review 43, 100924

Climate Action Plan 2019. City of Boston https://www.boston.gov/sites/default/files/imce-uploads/2019-10/city_of_boston_2019_climate_action_plan_update_2.pdf

Cook, Q., Argenio, K., Lovinsky-Desir, S. (2021). The impact of environmental injustice and social determinants of health on the role of air pollution in asthma and allergic disease in the United States, Journal of Allergy and Clinical Immunology 148, Issue 5, 1089-1101.e5, https://doi.org /10.1016/j.jaci.2021.09.018 .

Di, Q., Amini, H., Shi,,L ., Kloog , I., Silvern, R., Kelly,J ., Schwartz, J. (2019). An ensemble-based model of PM $_{2.5}$ concentration across the contiguous United States with high spatiotemporal resolution. Environment International 130, 104909, https://doi.org/10.1016/j.envint.2019.104909

EPA (2020). Health and Environmental Effects of Particulate Matter (PM). https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm

European Commission (2023). GHG emissions of all world countries 2023 report. https://edgar.jrc.ec.europa.eu/report_2023

Fong, K.C., Bell, M.L. (2021). Do fine particulate air pollution ($PM_{2.5}$) exposure and its attributable premature mortality differ for immigrants compared to those born in the United States?, Environmental Research 196, 110387, https://doi.org/10.1016/j.envres.2020.110387 .

Gil-Alana, L.A., Payne, J.E. (2020). Persistence, seasonality, and fractional integration within a nonlinear framework: Evidence from US citizens' overseas trave, Tourism Economics 28, 3.

Gil-Alana, L.A., Robinson, P.M. (1997). Testing of unit roots and other nonstationary hypotheses, Journal of Econometrics 80, 2, 241-268.

Gil-Alana, LA, Yaya, OS, Awolaja, O., Cristofaro , L. (2020a). Long Memory and Time Trends in Particulate Matter Pollution ($PM_{2.5}$ and PM_{10}) in the US States, Journal of Applied Meteorology and Climatology, 59(8), 1351-1367. https://doi.org/10.1175/JAMC-D-20-0040.1

Gil-Alana, LA, Yayá, OS, Carmona-González, N. (2020b) .Air quality in London: evidence of persistence, seasonality and trends, Theoretical and Applied Climatology 142, 103–115 https://doi.org/10.1007/s00704-020-03305-1

Global Carbon Atlas (2022). https://globalcarbonatlas.org/

Granger, C.W.J. (1980). Long memory relationships and the aggregation of dynamic models, Journal of Econometrics 14, 2, 227-238.

Granger, C. W. J. (1981). Some Properties of Time Series Data and Their Use in Econometric Model Specification. Journal of Econometrics, 16, 121-130. https://doi.org/10.1016/0304-4076(81)90079-8

Granger, C. W.J., Joyeux, R. (1980). An Introduction To Long-Memory Time Series Models And Fractional Differencing. *Journal of Time Series Analysis, 1*(1), 15-29. doi:10.1111/j.1467-9892.1980.tb00297.x+

Guan-Yu, L., Yi-Ming, L., Chuen-Jinn, T., Chia-Ying, L. (2022) Spatial-temporal characterization of air pollutants using a hybrid deep learning/Kriging model incorporated with a weather normalization technique, Atmospheric Environment 289, 119304, 352-2310, https://doi.org/10.1016/j.atmosenv.2022.119304 .

Habib, A. (2020). Exploring the physical interpretation of long-term memory in hydrology. Stoch Environ Res Risk Assess 34, 2083–2091. https://doi.org/10.1007/s00477-020-01883-0

Hadley, O. L. (2017). Background $PM_{2.5}$ source application in the remote northwestern United States. Atmospheric Environment 167, 298–308, https://doi.org/10.1016/j.atmosenv.2017.08.030

Hosking, J.R. (1981). Fractional differencing. Biometrika, 68, 165-176

IMF (2023). https://www.imf.org/es/Blogs/Articles/2023/10/02/emerging-economies-need-much-more-private-financing-for-climate-transition

Liu, H., Hao, H., Shi, L., Molinari, M. (2023). Air pollution associated with liver transplant outcomes in the United States, HPB 25, Supplement 1, S151, https://doi.org/10.1016/j.hpb.2023.05.289

Malik, AO, Jones, P.G., Chan, P.S. (2022). Association of ambient air pollution with risk of out of hospital cardiac arrest in the United States, American Heart Journal Plus: Cardiology Research and Practice 17, 100151, https://doi.org/10.1016/j.ahjo.2022.100151 .

Mei, C., Yongxu , C., Hongyu, Z., Youshuai , W., Yue, X. (2023) Analysis of pollutants transport in heavy air pollution processes using a new complex-network-based model, Atmospheric Environment 292, 19395, https://doi.org/10.1016/j.atmosenv.2022.119395

Muller, N.Z., Mendelsohn, R. (2007). Measuring the damages of air pollution in the United States., Journal of Environmental Economics and Management 54, Issue 1, 1-14, https://doi.org/10.1016/j.jeem.2006.12.002

Nadybal , S.M., Collins, T.W., Grineski , S.E. (2020). Light pollution inequities in the continental United States: A distributive environmental justice analysis, Environmental Research 189,109959, https://doi.org/10.1016/j.envres.2020.109959 .

Nelson, C.R. Plosser. C.I. (1982). Trends and random walks in macroeconomic time series: Some evidence and implications, Journal of Monetary Economics 10,2, 139-162.

Perez-Rodriguez, J.V., Rachinger, H., Santana-Gallego, M. (2020). Does tourism promote economic growth? A fractionally integrated heterogeneous panel data analysis, Tourism Economics 1-22.

Pokharel, A., Hennessy, D., Wu, F. (2023). Health burden associated with tillage-related $PM_{2.5}$ pollution in the United States, and mitigation strategies, Science of The Total Environment 903, 166161, https://doi.org/10.1016/j.scitotenv.2023.166161

Remigio, RV, Hao He, Raimann, JG, Kotanko , P., Maddux, F.W., Sapkota, AR, Liang, XZ Puett, R., He, X., Sapkota, A. (2022). Combined effects of air pollution and extreme heat events among ESKD patients within the Northeastern United States, Science of The Total Environment 812, 152481, https://doi.org/10.1016/j.scitotenv.2021.152481 .

Schennach, S.M. (2018). Long Memory via Networking. Econometrica. 86 (6): 2221–2248. doi:10.3982/ECTA11930. hdl:10419/189779.

Sullivan, TJ, Driscoll, CT, Beier, CM., Burtraw , D., Fernandez, IJ, Galloway, JN, Gay, DA, Goodale, CL Likens, GE, Lovett, GM, Watmough, SA(2018). Air pollution success stories in the United States: The value of long-term observations, Environmental Science & Policy 84, 69-73, https://doi.org/10.1016/j.envsci.2018.02.016 .

The White House (2023). Building a clean energy economy: a guidebook to the inflation reduction act's investments in clean energy and climate action. version 2.

https://www.whitehouse.gov/wp-content/uploads/2022/12/Inflation-Reduction-Act-Guidebook.pdf

The World Bank (2022). What You Need to Know About Climate Change and Air Pollution. https://www.worldbank.org/en/news/feature/2022/09/01/what-you-need-to-know-about-climate-change-and-air-pollution

World Air Quality Index (WAQI) in https://aqicn.org/map/world/es/ .

World Health Organization (2021). New WHO Global Air Quality Guidelines aim to save millions of lives from air pollution. https://www.who.int/news/item/22-09-2021-new-who-global-air-quality-guidelines-aim-to-save-millions-of-lives-from-air-pollution

Yuan, N., Franzke, C.L.E., Xiong, F., Fu, Z., Dong, W. (2022). The impact of long-term memory on the climate response to greenhouse gas emissions. *npj Clim Atmos Sci* 5, 70. https://doi.org/10.1038/s41612-022-00298-8

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Table 1: Estimates of the orders of integration

i) Original data			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
BOSTON	0.44 (0.40, 0.47)	0.42 (0.39, 0.46)	**0.42 (0.39, 0.46)**
CHICAGO	0.48 (0.44, 0.53)	**0.44 (0.39, 0.50)**	0.44 (0.39, 0.50)
DALLAS	0.55 (0.51, 0.59)	**0.54 (0.50, 0.58)**	0.54 (0.50, 0.58)
EL PASO	0.40 (0.38, 0.44)	**0.40 (0.37, 0.43)**	0.40 (0.37, 0.43)
LOS ANGELES	0.60 (0.56, 0.64)	**0.59 (0.54, 0.63)**	0.59 (0.54, 0.63)
NEW YORK	0.54 (0.51, 0.54)	**0.52 (0.49, 0.56)**	0.52 (0.49, 0.56)
SAN ANTONIO	0.49 (0.45, 0.53)	**0.47 (0.43, 0.51)**	0.47 (0.43, 0.51)
SEATTLE	0.67 (0.64, 0.72)	**0.67 (0.64, 0.72)**	0.67 (0.64, 0.72)
SAN JOSE	0.72 (0.68, 0.76)	**0.71 (0.67, 0.75)**	0.71 (0.67, 0.75)
PHOENIX	0.47 (0.45, 0.51)	**0.46 (0.43, 0.49)**	0.46 (0.43, 0.49)
i) Logged values			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
BOSTON	0.61 (0.55, 0.65)	0.41 (0.38, 0.44)	**0.40 (0.37, 0.43)**
CHICAGO	0.60 (0.55, 0.64)	**0.42 (0.38, 0.48)**	0.42 (0.38, 0.48)
DALLAS	0.57 (0.55, 0.60)	**0.50 (0.46, 0.54)**	0.50 (0.46, 0.54)
EL PASO	0.59 (0.54, 0.63)	**0.42 (0.39, 0.45)**	0.42 (0.39, 0.45)
LOS ANGELES	0.70 (0.64, 0.73)	**0.57 (0.53, 0.61)**	0.57 (0.53, 0.61)
NEW YORK	0.57 (0.54, 0.62)	**0.47 (0.44, 0.50)**	0.47 (0.44, 0.50)
SAN ANTONIO	0.55 (0.52, 0.58)	**0.43 (0.40, 0.47)**	0.43 (0.40, 0.47)
SEATTLE	0.67 (0.64, 0.70)	**0.57 (0.53, 0.61)**	0.57 (0.53, 0.61)
SAN JOSE	0.67 (0.64, 0.70)	**0.53 (0.49, 0.57)**	0.53 (0.49, 0.57)
PHOENIX	0.57 (0.54, 0.61)	**0.47 (0.44, 0.50)**	0.47 (0.44, 0.50)

Note: the reported values are the estimates of d with their corresponding 95% confidence intervals in brackets. In bold, the results for the best specification chosen on the basis of the statistical (in)significance of the deterministic terms.