Long Memory and Time Trends in Particulate Matter Pollution (PM_{2.5} and PM₁₀) in the 50 U.S. States

LUIS A. GIL-ALANA

Faculty of Economics, University of Navarra, Pamplona, and Universidad Francisco de Vitoria, Madrid, Spain

OLAOLUWA S. YAYA

Environmental Statistics Unit, Department of Statistics, University of Ibadan, Ibadan, Nigeria

OLADAPO G. AWOLAJA

Department of Economics, Babcock University, Ilishan-Remo, Nigeria

LORENZO CRISTOFARO

Faculty of Mathematics, University of Turin, Turin, Italy

(Manuscript received 3 March 2020, in final form 3 June 2020)

ABSTRACT

This paper focuses on the analysis of the time series behavior of the air quality in the 50 U.S. states by looking at the statistical properties of particulate matter (PM₁₀ and PM_{2.5}) datasets. We use long daily time series of outdoor air quality indices to examine issues such as the degree of persistence as well as the existence of time trends in data. For this purpose, we use a long-memory fractionally integrated framework. The results show significant negative time trend coefficients in a number of states and evidence of long memory in the majority of the cases. In general, we observe heterogeneous results across counties though we notice higher degrees of persistence in the states on the west with respect to those on the east, where there is a general decreasing trend. It is hoped that the findings in the paper will continue to assist in quantitative evidence-based air quality regulation and policies.

1. Introduction

Air quality in the United States has undergone a dramatic shift since 2016 when the level of particulate matter (particulate pollution) increased by 5.5% during the 2016–18 time period, according to U.S. Environmental Protection Agency (EPA) datasets. In a report by the National Bureau of Economic Research, the worsening of air quality in the United States is due to more wildfires, more economic growth, and less enforcement of federal regulations (Clay and Muller 2019). Particulate matter is in the form of solid particles and liquid droplets such as dust, dirt, and soot smoke with fine or coarse sizes. Two types of particulate matter are PM₁₀ and PM_{2.5}; the former is coarse particulate with particles of diameter 10 μm , and the latter is fine particulate with particles of diameter 2.5 μm . These particles are emitted

from construction sites, automobiles, unpaved roads, fields, smokestacks, or fires.

Among the pollutants, PM_{2.5} is known to increase premature mortality risk (EPA 2011; Muller et al. 2011). PM_{2.5} is majorly of concern to regulators and public health experts because of its microscopic size, which aids easier inhaling and absorption into the bloodstream relative to the coarse type PM₁₀. Exposure of humans to particles can affect lungs and hearts, causing premature death, heart attacks, asthma, and other lung and respiratory malfunctioning (EPA 2018). Fine particles easily accumulate in the brain, and this is linked to dementia and cognitive decline in adults; also these particles are the main cause of haze in many parts of the United States.

The Air Quality Index (AQI) gives the level of cleanliness of outdoor air, and data are synchronized daily. From these datasets, the EPA monitors the emission of pollutants using national and regional rules.

Corresponding author: Luis A. Gil-Alana, alana@unav.es

DOI: 10.1175/JAMC-D-20-0040.1

© 2020 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](https://www.ametsoc.org/PUBSReuseLicenses) (www.ametsoc.org/PUBSReuseLicenses).

Air quality in the United States has improved significantly as a result of policies of the EPA and the World Health Organization (WHO; Pope et al. 2009). The effort was largely due to the health hazard posed by $\text{PM}_{2.5}$ (Dockery et al. 1993; Pope et al. 2002); in 2015, about 9% of the Americans lived in counties with concentrations of $\text{PM}_{2.5}$ above the WHO AQI standard of $10 \mu\text{g m}^{-3}$ and 89% lived in counties with concentrations of $5\text{--}10 \mu\text{g m}^{-3}$. Thus, further reducing $\text{PM}_{2.5}$ will likely lower mortality caused by these health hazards.

Studying the dynamics of values of PM_{10} and $\text{PM}_{2.5}$ in the U.S. case informs researchers and policymakers about life expectancy in their respective U.S. counties or states. The literature we present in this paper comprises epidemiological studies (Choi et al. 2018; Lee et al. 2019), studies on pollutant concentration and seasonal variations in the dynamics of particulate pollution (Pryor and Barthelmie 1996; Pillai et al. 2002), studies relating pollutants to climate change (Tai et al. 2010), and studies on the causes of air pollution (see, e.g., Ji et al. 2018). There also exists sparse literature on factors influencing exposure to air pollutants. The epidemiological studies investigate the existence of a relationship between human health-related problems and exposure to air pollution. There are several strands of evidence from epidemiological research supporting health-related problems induced by exposure to air pollutants (Li et al. 2019). According to the report by the WHO, fine particulate matter is one of the air pollutants that is associated with a large number of health issues (WHO 2013a,b). Shou et al. (2019) examine exposure to $\text{PM}_{2.5}$ and the risk of neurodegenerative diseases. They provide evidence that $\text{PM}_{2.5}$ induces neurodegenerative diseases. $\text{PM}_{2.5}$ has also been found to induce respiratory problems (Choi et al. 2018; Weinmayr et al. 2018; Wu et al. 2018). Maji et al. (2018) reveal evidence linking $\text{PM}_{2.5}$ to cardiovascular diseases.

Pillai et al. (2002) examine the concentration of $\text{PM}_{2.5}$ and PM_{10} . From their results, PM_{10} concentration is lower than limits given by various environmental standards, while $\text{PM}_{2.5}$ exceeds the threshold set by the U.S. EPA. There is also seasonal variation in $\text{PM}_{2.5}$ and PM_{10} with the highest concentration during the winter season. Pryor and Barthelmie (1996) found that PM_{10} concentration in Canada is above the standard set in California (United States), even though it passes the WHO threshold. Ji et al. (2018) examine the socioeconomic drivers of $\text{PM}_{2.5}$ in 79 developing economies and findings from the study indicate that income, urbanization, and the service sector have a significant impact on $\text{PM}_{2.5}$ concentration. There also exists an inverted U relationship between urbanization and $\text{PM}_{2.5}$ in which the particulate matter

positively correlates with a low-income level or urbanization but has a negative association at a high level. Chu and Paisie (2006) evaluate the current $\text{PM}_{2.5}$ situation using the critical design values application. Their findings suggest that California and some areas in the east stand the risk of potential future violation of the annual threshold for $\text{PM}_{2.5}$ set by the National Ambient Air Quality Standards. Also, the 24-h standard is likewise at the risk of being violated by California and some areas in the west. Bell et al. (2007) reveal findings supporting strong and geographic variations in the concentrations of $\text{PM}_{2.5}$ in the United States. Tai et al. (2010) investigate the response of fine particulate matter ($\text{PM}_{2.5}$) to meteorological variables using a multiple linear regression model; the study employs observational data for the period from 1998 to 2008. The concentration of $\text{PM}_{2.5}$ and its various components are found to have an association with meteorological variables except for temperature, relative humidity, and wind direction. Evidence reveals that climate change has potential effects on $\text{PM}_{2.5}$. Other similar studies are Liao et al. (2006), Racherla and Adams (2006), Tagaris et al. (2007), Avise et al. (2009), and Pye et al. (2009); the studies used a general circulation model–chemical transport model to simulate air pollutants concentrations.

Hadley (2017) identifies marine-traffic residual fuel oil (RFO), biomass combustion emissions (BMC), seawater, and crustal materials as explaining the concentrations of $\text{PM}_{2.5}$ in the northwestern United States. The study makes use of a matrix factorization model by the U.S. EPA to analyze seasonal and long-term trends. From January 2011 to December 2014, the period covered in the study, the effects of RFO were highest during late summer, while BMC and sea salt contributed the largest in winter. The crustal material does not indicate any seasonal cycle. De Jesus et al. (2019) examine the ultrafine particles and $\text{PM}_{2.5}$ for 10 cities located in North America, Europe, Asia, and Australia for over 12 months. The seasonal variation in air pollutants is found to be associated with geographical locations of the cities and their features. Di et al. (2019) examine the concentration of $\text{PM}_{2.5}$ across the contiguous United States from 2000 to 2015. Findings show that the $\text{PM}_{2.5}$ prediction dataset allows an accurate estimate of the adverse effect of $\text{PM}_{2.5}$ on health by epidemiologists.

The long-memory feature in the air pollutant series has been previously studied by some authors. Thus, for example, Chen et al. (2016) examined four major cities in China—Beijing, Shanghai, Guangzhou, and Shenzhen—with data between 2013 and 2015 and found high level of persistence in the four cities, especially in

TABLE 1. Data description and sample. State abbreviations can be found in [Table A1](#) of [appendix A](#).

No.	State	PM _{2.5}		PM ₁₀	
		Start date	End date	Start date	End date
1	AL	6 Jan 1999	3 Dec 2019	2 Jan 1999	26 Jul 2019
2	AK	10 Apr 1999	5 Dec 2019	6 Jan 1999	30 Jun 2019
3	AZ	6 Jan 1999	5 Dec 2019	1 Jan 1999	30 Sep 2019
4	AR	30 Jun 1999	5 Dec 2019	6 Jan 1999	30 Sep 2019
5	CA	3 Jan 1999	5 Dec 2019	1 Jan 1999	30 Sep 2019
6	CO	1 Jan 1999	5 Dec 2019	1 Jan 1999	1 Sep 2019
7	CT	9 Jan 1999	5 Dec 2019	1 Jan 1999	30 Sep 2019
8	DE	3 Jan 1999	5 Dec 2019	6 Jan 1999	30 Sep 2019
9	FL	3 Jan 1999	5 Dec 2019	1 Jan 1999	30 Jul 2003
10	GA	1 Jan 1999	5 Dec 2019	1 Jan 1999	31 Aug 2019
11	HI	19 Jan 2001	5 Dec 2019	1 Jan 1999	30 Sep 2019
12	ID	3 Jan 1999	5 Dec 2019	1 Jan 1999	30 Jun 2019
13	IL	7 Jan 1999	5 Dec 2019	13 Jan 1999	26 Dec 2000
14	IN	22 Jan 1999	5 Dec 2019	6 Jan 1999	30 Sep 2019
15	IA	5 Feb 1999	5 Dec 2019	4 Jan 1999	30 Sep 2019
16	KS	27 Jan 1999	5 Dec 2019	18 Jan 1999	30 Jun 2019
17	KY	30 Jan 1999	8 Nov 2011	6 Jan 1999	31 Dec 2005
18	LA	1 Jan 1999	17 Nov 2019	6 Jan 1999	31 Jan 2019
19	ME	5 Jun 2015	14 Jun 2019	6 Jan 1999	14 Jun 2019
20	MD	12 May 1999	5 Dec 2019	6 Jan 1999	26 Jun 2019
21	MA	3 Jan 1999	5 Dec 2019	6 Jan 1999	16 Jul 2019
22	MI	15 Jan 1999	5 Dec 2019	6 Jan 1999	26 Mar 2001
23	MN	8 Nov 1999	30 Jun 2001	3 Oct 1999	27 Sep 2000
24	MS	14 Feb 1999	5 Dec 2019	1 Jan 1999	31 Oct 2019
25	MO	2 Apr 2002	28 Jun 2006	3 Jan 1999	30 Sep 2019
26	MT	9 Jan 1999	6 Dec 2019	1 Jan 1999	26 Dec 2008
27	NE	3 Jan 1999	30 Sep 2019	3 Jan 1999	30 Jun 2019
28	NV	1 Apr 2003	6 Dec 2019	1 Jan 1999	30 Jun 2019
29	NH	6 Jan 1999	31 Dec 2014	6 Jan 1999	28 Dec 2002
30	NJ	3 Jan 1999	6 Dec 2019	6 Jan 1999	28 Mar 2011
31	NM	6 Jan 1999	6 Dec 2019	2 Jan 1999	12 Apr 2015
32	NY	2 Jul 1999	6 Dec 2019	6 Jan 1999	29 Mar 2005
33	NC	1 Jan 1999	6 Dec 2019	6 Jan 1999	30 Sep 2019
34	ND	20 Feb 1999	6 Dec 2019	7 Jan 2001	30 Sep 2019
35	OH	1 Jan 1999	6 Dec 2019	1 Jan 1999	30 Sep 2019
36	OK	1 Apr 1999	6 Dec 2019	1 Jan 2000	31 Oct 2019
37	OR	1 Jan 1999	6 Dec 2019	1 Jan 1999	31 Mar 2019
38	PA	1 Jan 1999	6 Dec 2019	2 Aug 2000	11 Jun 2019
39	RI	3 Jan 1999	6 Dec 2019	6 Jan 1999	30 Sep 2019
40	SC	3 Jan 1999	6 Dec 2019	1 Jan 1999	30 Sep 2019
41	SD	1 Jan 2015	6 Dec 2019	3 Jan 1999	30 Jun 2019
42	TN	1 Jan 1999	6 Dec 2019	3 Jan 1999	13 Jun 2019
43	TX	12 Mar 1999	6 Dec 2019	21 Oct 1999	26 Jun 2019
44	UT	1 Jan 1999	6 Dec 2019	1 Jan 1999	31 Oct 2019
45	VT	3 Jan 1999	6 Dec 2019	6 Feb 1999	26 Jun 2019
46	VA	27 Jan 1999	30 Sep 2019	6 Jan 1999	5 Nov 2019
47	WA	3 Jan 1999	6 Dec 2019	6 Jan 1999	29 Apr 2006
48	WV	3 Jan 1999	12 Nov 2019	6 Jan 1999	22 Dec 2015
49	WI	3 Jan 1999	6 Dec 2019	6 Jan 1999	31 Aug 2019
50	WY	6 Jan 1999	6 Dec 2019	6 Jan 1999	30 Sep 2019

Guangzhou and Shenzhen. [Meraz et al. \(2015\)](#) used re-scaled range (R/S) analysis and found evidence of long-range dependence in the air pollutants in Mexico City, Mexico, although this property was not found to be uniform across time scales. Other articles using the R/S

method in the analysis of air pollutants include [Chelani \(2009, 2016\)](#), [Meraz et al. \(2015\)](#), and [Nikolopoulos et al. \(2019\)](#). Other studies have used other nonparametric methods such as the detrended fluctuation analysis (DFA) ([Varotsos et al. 2005](#)) and its generalization, the

FIG. 1. Time plots of fine and coarse particulate matter [(top) $PM_{2.5}$ and (bottom) PM_{10}] for only (left) Alabama and (right) Wyoming (the other 48 U.S. states cannot be represented because of space, but the plots are available upon request).

multifractal detrended fluctuation analysis (MF-DFA) (Xue et al. 2015), estimating the Hurst parameter (Hurst 1951) and its potential change over time. Given the sensitiveness of these methods to the user-chosen parameters and the need for a large amount of data to obtain reliable estimates (Kantelhardt et al. 2002; Thompson and Wilson 2016), the fractional integration model is a useful approach with which to get reliable results for relatively short time series such as those employed in this work. Although R/S analysis, DFA, MF-DFA, and the fractional integration take long memory into account, they are closely linked (see Beran 1994).

Our approach to the analysis of particulate pollutants is based on the analysis of the time series properties of the two pollutants (PM_{10} and $PM_{2.5}$) by looking at its long-memory structure. Findings from this paper will be useful in the econometric modeling of pollutant variables with other macroeconomic, health-related, and demographic variables. Previous literature lacks knowledge of the time series properties of pollutant levels in the zones/cities under consideration. Specifically, we investigate the time series properties in PM_{10} and $PM_{2.5}$ series in each U.S. state using fractional integration. The methodological approach employed in this work allows for fractional values in the degree of differentiation of the

series, to render them stationary $I(0)$, such that the degree of differentiation of the series (the persistence parameter) takes value in the long-memory range. This allows us to have a much richer degree of flexibility in the dynamic specification of the data compared with the classical case of unit roots or more generally integer degrees of differentiation. In addition, the fractional integration framework allows for potential deterministic trends in order to determine if there is a systematic pattern in the data across time. The kind of time series analysis approach employed in this work is novel and has been rarely applied in the analysis of air quality datasets since it is also a mandatory step in the Box–Jenkins time series modeling (see Box et al. 2015). Furthermore, this approach provides a useful economic interpretation for air quality regulatory agencies regarding policy formation.

The contribution of this work is twofold: first, we investigate whether long memory is a feature observed in the particulate matter pollution data in the United States and for this purpose we use a parametric approach based on fractional integration methods. Second, and based on the previous feature, we investigate whether time trends are present in the data and whether the time trend coefficient changes according to this long-memory feature. Implications of the results obtained are presented in the final part of the paper.

The rest of the paper is structured as follows: [section 2](#) presents the statistical methods applied in the paper and describes the datasets. [Section 3](#) displays the main empirical results, and [section 4](#) renders the conclusions and policy recommendations.

2. Materials and methods

a. Statistical method

During the analysis of time series, a crucial issue is to determine if the series is stationary or not. With non-stationary series, a standard approach is to take first differences, that is, if the original series, x_t , is non-stationary but its first differences, $y_t = x_t - x_{t-1}$ produce a stationary series. Then, we say that x_t is integrated of order 1 or $I(1)$. This concept has been generalized to the fractional case, and a time series can be integrated of order d or $I(d)$ where d is a fractional value. In other words, we say that a time series x_t is integrated of order d if it can be expressed as

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \dots, \quad (1)$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is the $I(0)$ series, defined for our purposes as a covariance (or second order) stationary process with a spectral density function that is positive and finite at the zero frequency. The polynomial $(1 - L)^d$ in the left-hand side of Eq. (1) can be expressed in terms of its binomial expansion, such that, for all real d ,

$$\begin{aligned} (1 - L)^d &= \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j \\ &= 1 - dL + \frac{d(d-1)}{2} L^2 - \frac{d(d-1)(d-2)}{6} L^3 \dots, \end{aligned}$$

and thus

$$\begin{aligned} (1 - L)^d x_t &= x_t - dx_{t-1} + \frac{d(d-1)}{2} x_{t-2} \\ &\quad - \frac{d(d-1)(d-2)}{6} x_{t-3} + \dots. \end{aligned} \quad (2)$$

Therefore, if d is not an integer, x_t depends on all of its past history, and if $d > 0$, x_t displays the property of long memory, based on the large degree of dependence between observations that are far apart. The concept of long memory is more general than fractional integration since it refers to the property that the spectral density function contains at least one singularity or pole in the interval $[0, \pi)$. In the case

TABLE 2. Data summary and category.

No.	State	PM _{2.5}			PM ₁₀		
		Mean	Min	Max	Mean	Min	Max
1	AL	47.54	0	221	18.30	0	66
2	AK	26.68	0	145	7.84	0	42.0
3	AZ	52.18	6	249	78.22	5.0	2212.0
4	AR	48.79	4	235	20.12	2.0	60.7
5	CA	51.88	4	314	22.25	3.0	169.0
6	CO	40.12	0	195	32.49	2.0	103.0
7	CT	38.90	0	158	50.22	0.0	70.0
8	DE	37.36	0	181	22.41	1.0	168
9	FL	45.85	0	326	15.09	3.0	71.00
10	GA	58.59	6	197	20.33	0.0	99.0
11	HI	48.82	0	172	17.06	5.0	121.00
12	ID	42.13	0	243	23.94	1.0	215.0
13	IL	41.30	4	124	21.03	4.0	64.0
14	IN	56.25	10	191	20.35	0	75
15	IA	38.65	3	138	21.57	1.0	92
16	KS	38.26	0	158	18.85	0.00	80.00
17	KY	47.96	4	144	16.20	1.0	51.00
18	LA	51.20	8	181	24.10	3.0	99
19	ME	22.92	3	80	13.52	0	73
20	MD	51.85	2	169	20.42	0	70
21	MA	50.19	0	172	14.77	1.0	67.0
22	MI	37.53	1	144	22.5	58.0	6.0
23	MN	45.68	4	106	22.05	8.0	59
24	MS	46.49	10	168	19.17	4	79
25	MO	44.80	1	113	25.37	506	0
26	MT	32.71	0	171	19.54	1	104
27	NE	34.04	0	168	18.90	89.0	1.0
28	NV	23.48	0	220	21.30	1.0	4.0
29	NH	35.74	0	151	13.51	0	56
30	NJ	57.38	12	167	20.03	1	86
31	NM	15.87	0	109	11.42	1	65
32	NY	34.72	0	162	10.24	0	60.0
33	NC	47.30	0	173	16.31	0	76
34	ND	27.82	0	198	14.35	0	156
35	OH	48.10	2	208	23.75	0	93
36	OK	41.41	3	152	19.86	0	86
37	OR	26.81	0	170	21.25	0	122.0
38	PA	50.71	3	187	16.70	1	89
39	RI	42.20	0	170	19.29	2	71
40	SC	45.72	0	253	26.38	1.0	130
41	SD	16.20	0	152	18.54	0	125.0
42	TN	49.77	5	154	19.41	2	64
43	TX	39.29	5	152	18.82	3	73
44	UT	44.41	5	171	30.6	2.0	501
45	VT	36.58	0	160	13.80	0	65
46	VA	44.07	2	152	14.90	2	100
47	WA	29.72	2	173	13.33	3	53
48	WV	47.93	0	162	17.04	0	77
49	WI	40.13	0	154	16.20	0	70
50	WY	18.66	0	160	12.23	0	82

of a model like Eq. (1), the singularity occurs at the smallest (zero) frequency.

In this context of fractional integration or $I(d)$ processes, the differencing parameter d is crucial on several fronts. For instance, if $d = 0$, the process is

TABLE 3. Estimated d coefficients and 95% confidence bands for PM₁₀. Confidence limits are given in parentheses. Boldface type indicates the selected specification for each case according to the t values of the estimated coefficients.

No.	State	No terms	An intercept	A linear time trend
1	AL	0.32 (0.29, 0.35)	0.29 (0.26, 0.33)	0.29 (0.26, 0.33)
2	AK	0.24 (0.20, 0.28)	0.23 (0.19, 0.27)	0.23 (0.19, 0.27)
3	AZ	0.28 (0.27, 0.30)	0.29 (0.27, 0.31)	0.29 (0.27, 0.31)
4	AR	0.31 (0.28, 0.33)	0.23 (0.20, 0.26)	0.19 (0.16, 0.23)
5	CA	0.45 (0.43, 0.48)	0.45 (0.42, 0.47)	0.45 (0.42, 0.47)
6	CO	0.41 (0.39, 0.43)	0.40 (0.38, 0.42)	0.40 (0.38, 0.43)
7	CT	0.34 (0.31, 0.37)	0.30 (0.27, 0.33)	0.30 (0.27, 0.33)
8	DE	0.29 (0.27, 0.31)	0.26 (0.24, 0.28)	0.26 (0.23, 0.28)
9	FL	0.49 (0.44, 0.53)	0.47 (0.42, 0.52)	0.47 (0.42, 0.52)
10	GA	0.40 (0.38, 0.43)	0.38 (0.36, 0.41)	0.38 (0.36, 0.41)
11	HI	0.41 (0.39, 0.43)	0.40 (0.38, 0.43)	0.40 (0.38, 0.43)
12	ID	0.49 (0.46, 0.51)	0.48 (0.45, 0.50)	0.48 (0.45, 0.50)
13	IL	0.21 (0.10, 0.39)	0.26 (0.15, 0.41)	0.22 (0.09, 0.40)
14	IN	0.34 (0.31, 0.36)	0.29 (0.26, 0.32)	0.28 (0.25, 0.31)
15	IA	0.34 (0.32, 0.37)	0.31 (0.29, 0.34)	0.31 (0.28, 0.34)
16	KS	0.46 (0.44, 0.49)	0.45 (0.42, 0.48)	0.45 (0.42, 0.48)
17	KY	0.50 (0.46, 0.55)	0.48 (0.44, 0.53)	0.48 (0.44, 0.53)
18	LA	0.43 (0.40, 0.46)	0.40 (0.37, 0.43)	0.40 (0.37, 0.43)
19	ME	0.30 (0.27, 0.34)	0.25 (0.21, 0.29)	0.23 (0.18, 0.27)
20	MD	0.31 (0.28, 0.34)	0.25 (0.22, 0.28)	0.22 (0.19, 0.25)
21	MA	0.32 (0.31, 0.34)	0.27 (0.25, 0.29)	0.22 (0.20, 0.25)
22	MI	0.07 (−0.02, 0.29)	0.09 (−0.04, 0.27)	0.08 (−0.05, 0.27)
23	MN	0.18 (−0.14, 0.45)	0.06 (−0.09, 0.26)	0.07 (−0.08, 0.28)
24	MS	0.47 (0.43, 0.52)	0.46 (0.41, 0.51)	0.46 (0.41, 0.51)
25	MO	0.25 (0.23, 0.27)	0.22 (0.20, 0.25)	0.22 (0.19, 0.24)
26	MT	0.41 (0.37, 0.44)	0.40 (0.37, 0.44)	0.40 (0.37, 0.44)
27	NE	0.40 (0.38, 0.43)	0.39 (0.36, 0.41)	0.39 (0.36, 0.41)
28	NV	0.44 (0.42, 0.47)	0.44 (0.41, 0.46)	0.44 (0.41, 0.46)
29	NH	0.22 (0.09, 0.34)	0.15 (0.06, 0.27)	0.15 (0.05, 0.27)
30	NJ	0.23 (0.18, 0.28)	0.19 (0.14, 0.24)	0.19 (0.14, 0.24)
31	NM	0.31 (0.27, 0.35)	0.27 (0.23, 0.32)	0.27 (0.23, 0.32)
32	NY	0.27 (0.20, 0.34)	0.26 (0.19, 0.33)	0.26 (0.19, 0.33)
33	NC	0.46 (0.44, 0.49)	0.44 (0.42, 0.48)	0.44 (0.41, 0.48)
34	ND	0.49 (0.46, 0.52)	0.49 (0.46, 0.51)	0.48 (0.46, 0.50)
35	OH	0.38 (0.35, 0.41)	0.37 (0.34, 0.40)	0.37 (0.34, 0.40)
36	OK	0.39 (0.36, 0.42)	0.37 (0.33, 0.40)	0.37 (0.33, 0.40)
37	OR	0.45 (0.40, 0.50)	0.43 (0.38, 0.48)	0.43 (0.38, 0.48)
38	PA	0.47 (0.44, 0.50)	0.45 (0.42, 0.49)	0.45 (0.42, 0.49)
39	RI	0.29 (0.26, 0.32)	0.21 (0.18, 0.24)	0.16 (0.13, 0.21)
40	SC	0.40 (0.38, 0.42)	0.36 (0.33, 0.39)	0.34 (0.31, 0.37)
41	SD	0.37 (0.35, 0.40)	0.35 (0.33, 0.38)	0.35 (0.33, 0.38)
42	TN	0.37 (0.35, 0.40)	0.33 (0.30, 0.35)	0.30 (0.27, 0.33)
43	TX	0.26 (0.22, 0.30)	0.20 (0.16, 0.24)	0.20 (0.16, 0.24)
44	UT	0.40 (0.37, 0.42)	0.38 (0.35, 0.40)	0.37 (0.35, 0.40)
45	VT	0.22 (0.19, 0.27)	0.15 (0.11, 0.19)	0.10 (0.06, 0.15)
46	VA	0.31 (0.28, 0.33)	0.22 (0.20, 0.26)	0.22 (0.20, 0.26)
47	WA	0.23 (0.14, 0.32)	0.17 (0.10, 0.25)	0.17 (0.10, 0.25)
48	WV	0.49 (0.46, 0.52)	0.47 (0.44, 0.51)	0.47 (0.44, 0.51)
49	WI	0.30 (0.26, 0.33)	0.23 (0.19, 0.27)	0.21 (0.17, 0.25)
50	WY	0.39 (0.36, 0.41)	0.38 (0.35, 0.40)	0.38 (0.35, 0.40)

stationary and short memory, with little dependence between the observations and with shocks disappearing fast. If d belongs to the interval $(0, 0.5)$, x_t is still covariance stationary though with long memory and mean-reverting properties, and the effects of the shocks disappear, at a relatively slower rate; if d

belongs to the interval $[0.5, 1)$, the series is no longer stationary but shocks are still mean reverting, although with long-lasting effects; $d = 1$ refers to the classical $I(1)$ case, and values of $d \geq 1$ also imply lack of mean reversion. Thus, by using fractional values for the differencing parameter, we allow for a much

TABLE 4. Estimated coefficients for each series for PM₁₀. Confidence limits of d are given in parentheses in the third column, and t statistic estimates for intercept and trend coefficients are given in parentheses in the fourth and fifth columns, respectively.

No.	State	No terms	An intercept	A linear time trend
1	AL	0.29 (0.26, 0.33)	17.2796 (11.61)	—
2	AK	0.23 (0.19, 0.27)	7.8790 (11.57)	—
3	AZ	0.29 (0.27, 0.31)	70.2758 (6.61)	—
4	AR	0.19 (0.16, 0.23)	26.5720 (21.83)	−0.007 01 (−6.02)
5	CA	0.45 (0.42, 0.47)	24.3394 (6.59)	—
6	CO	0.40 (0.38, 0.42)	20.2032 (11.58)	—
7	CT	0.30 (0.27, 0.33)	19.1985 (9.72)	−0.002 28 (−1.81)
8	DE	0.26 (0.23, 0.28)	26.5493 (16.18)	−0.001 16 (−2.88)
9	FL	0.47 (0.42, 0.52)	13.0903 (4.96)	—
10	GA	0.38 (0.36, 0.41)	23.2157 (9.22)	−0.001 08 (−1.66)
11	HI	0.40 (0.38, 0.43)	22.2647 (10.53)	−0.000 95 (−1.80)
12	ID	0.48 (0.45, 0.50)	28.5326 (6.04)	—
13	IL	0.22 (0.09, 0.40)	14.3576 (3.72)	0.105 60 (1.90)
14	IN	0.28 (0.25, 0.31)	25.7129 (13.71)	−0.002 37 (−2.95)
15	IA	0.31 (0.28, 0.34)	25.6919 (10.28)	−0.002 42 (−2.08)
16	KS	0.45 (0.42, 0.48)	20.1905 (6.37)	—
17	KY	0.48 (0.44, 0.53)	15.5667 (5.28)	—
18	LA	0.40 (0.37, 0.43)	28.6425 (9.04)	−0.002 45 (−1.75)
19	ME	0.23 (0.18, 0.27)	20.0008 (10.94)	−0.010 20 (−3.97)
20	MD	0.22 (0.19, 0.25)	28.4817 (17.34)	−0.007 62 (−5.79)
21	MA	0.22 (0.20, 0.25)	25.0263 (22.77)	−0.006 06 (−10.39)
22	MI	0.09 (−0.04, 0.27)	22.3934 (13.14)	—
23	MN	0.06 (−0.09, 0.26)	22.1955 (13.27)	—
24	MS	0.46 (0.41, 0.51)	17.4952 (5.25)	—
25	MO	0.22 (0.19, 0.24)	30.8592 (14.11)	−0.001 63 (−2.95)
26	MT	0.40 (0.37, 0.44)	17.1230 (5.18)	—
27	NE	0.39 (0.36, 0.41)	19.2983 (6.68)	—
28	NV	0.44 (0.41, 0.46)	18.8045 (4.98)	—
29	NH	0.15 (0.06, 0.27)	13.6835 (11.34)	—
30	NJ	0.19 (0.14, 0.24)	19.8264 (15.39)	—
31	NM	0.27 (0.23, 0.32)	11.0846 (12.41)	—
32	NY	0.26 (0.19, 0.33)	9.9455 (6.27)	—
33	NC	0.44 (0.42, 0.48)	17.8403 (7.62)	—
34	ND	0.49 (0.46, 0.51)	12.7550 (3.78)	—
35	OH	0.37 (0.34, 0.40)	21.9157 (7.73)	—
36	OK	0.37 (0.33, 0.40)	21.3063 (8.94)	—
37	OR	0.43 (0.38, 0.48)	27.3899 (5.35)	—
38	PA	0.45 (0.42, 0.49)	18.9998 (6.74)	—
39	RI	0.16 (0.13, 0.21)	26.8347 (21.21)	−0.011 26 (−6.90)
40	SC	0.34 (0.31, 0.37)	42.0332 (13.48)	−0.004 26 (−5.69)
41	SD	0.35 (0.33, 0.38)	18.5579 (7.76)	—
42	TN	0.30 (0.27, 0.33)	25.7787 (13.43)	−0.006 46 (−4.43)
43	TX	0.20 (0.16, 0.24)	19.1547 (20.95)	—
44	UT	0.37 (0.35, 0.40)	39.1423 (8.63)	−0.002 59 (−2.36)
45	VT	0.10 (0.06, 0.15)	17.3939 (21.27)	−0.006 61 (−5.15)
46	VA	0.22 (0.20, 0.26)	19.3022 (17.24)	−0.005 00 (−4.79)
47	WA	0.17 (0.10, 0.25)	13.3469 (14.03)	—
48	WV	0.47 (0.44, 0.51)	16.2894 (5.40)	—
49	WI	0.21 (0.17, 0.25)	19.4885 (14.56)	−0.005 28 (−2.93)
50	WY	0.38 (0.35, 0.40)	12.9041 (7.30)	—

richer structure in the dynamic specification of the data. Thus, classical methods based on autoregressive (integrated) moving average [AR(I)MA] models only consider the stationary autoregressive moving average (ARMA) case that imposes $d = 0$ and the non-stationary ARIMA case with $d = 1$ and do not consider

the fractional alternatives employed in this work. In addition, it is well known that the standard (unit root) methods that distinguish between stationarity and non-stationarity (i.e., [Dickey and Fuller 1979](#); [Phillips and Perron 1988](#); [Kwiatkowski et al. 1992](#); [Elliott et al. 1996](#)) have very low power if the true data-generating process

TABLE 5. Estimated d coefficients and 95% confidence bands for PM_{2.5}. Confidence limits are given in parentheses. Boldface type indicates the selected specification for each case according to the t values of the estimated coefficients.

No.	State	No terms	An intercept	A linear time trend
1	AL	0.40 (0.37, 0.42)	0.35 (0.32, 0.38)	0.35 (0.32, 0.37)
2	AK	0.48 (0.45, 0.51)	0.48 (0.45, 0.51)	0.48 (0.45, 0.51)
3	AZ	0.34 (0.32, 0.36)	0.32 (0.30, 0.33)	0.31 (0.30, 0.33)
4	AR	0.46 (0.43, 0.48)	0.42 (0.40, 0.45)	0.42 (0.40, 0.45)
5	CA	0.55 (0.53, 0.55)	0.55 (0.52, 0.57)	0.55 (0.52, 0.57)
6	CO	0.35 (0.33, 0.37)	0.33 (0.30, 0.35)	0.33 (0.30, 0.35)
7	CT	0.39 (0.36, 0.41)	0.36 (0.34, 0.39)	0.36 (0.34, 0.39)
8	DE	0.31 (0.29, 0.34)	0.26 (0.24, 0.28)	0.23 (0.21, 0.26)
9	FL	0.42 (0.40, 0.45)	0.39 (0.36, 0.42)	0.39 (0.36, 0.42)
10	GA	0.43 (0.41, 0.46)	0.40 (0.37, 0.42)	0.39 (0.37, 0.42)
11	HI	0.46 (0.44, 0.48)	0.46 (0.44, 0.48)	0.46 (0.44, 0.48)
12	ID	0.51 (0.48, 0.53)	0.50 (0.48, 0.53)	0.50 (0.48, 0.53)
13	IL	0.28 (0.26, 0.31)	0.20 (0.18, 0.23)	0.16 (0.13, 0.20)
14	IN	0.48 (0.45, 0.51)	0.45 (0.42, 0.49)	0.45 (0.42, 0.49)
15	IA	0.49 (0.46, 0.55)	0.47 (0.44, 0.51)	0.47 (0.44, 0.50)
16	KS	0.32 (0.29, 0.34)	0.26 (0.23, 0.29)	0.25 (0.22, 0.29)
17	KY	0.30 (0.28, 0.33)	0.23 (0.20, 0.27)	0.22 (0.19, 0.26)
18	LA	0.48 (0.45, 0.50)	0.45 (0.42, 0.48)	0.45 (0.42, 0.48)
19	ME	0.21 (0.11, 0.31)	0.14 (0.06, 0.24)	0.12 (0.05, 0.22)
20	MD	0.45 (0.42, 0.48)	0.42 (0.39, 0.45)	0.41 (0.38, 0.45)
21	MA	0.37 (0.35, 0.39)	0.33 (0.31, 0.33)	0.32 (0.30, 0.35)
22	MI	0.27 (0.25, 0.29)	0.20 (0.18, 0.22)	0.17 (0.15, 0.20)
23	MN	0.16 (−0.05, 0.44)	0.10 (−0.06, 0.33)	0.10 (−0.06, 0.33)
24	MS	0.48 (0.45, 0.51)	0.45 (0.42, 0.48)	0.45 (0.42, 0.48)
25	MO	0.24 (0.17, 0.32)	0.14 (0.08, 0.22)	0.14 (0.08, 0.22)
26	MT	0.51 (0.48, 0.53)	0.50 (0.48, 0.53)	0.50 (0.48, 0.53)
27	NE	0.25 (0.23, 0.28)	0.19 (0.16, 0.22)	0.17 (0.14, 0.20)
28	NV	0.64 (0.60, 0.68)	0.64 (0.60, 0.68)	0.64 (0.60, 0.68)
29	NH	0.20 (0.17, 0.24)	0.14 (0.11, 0.17)	0.13 (0.10, 0.16)
30	NJ	0.39 (0.36, 0.41)	0.35 (0.32, 0.38)	0.35 (0.32, 0.37)
31	NM	0.40 (0.38, 0.42)	0.38 (0.36, 0.40)	0.38 (0.36, 0.40)
32	NY	0.35 (0.33, 0.37)	0.31 (0.29, 0.34)	0.31 (0.28, 0.33)
33	NC	0.45 (0.43, 0.48)	0.43 (0.40, 0.46)	0.43 (0.40, 0.46)
34	ND	0.40 (0.38, 0.43)	0.39 (0.36, 0.42)	0.38 (0.36, 0.41)
35	OH	0.43 (0.41, 0.45)	0.39 (0.36, 0.42)	0.38 (0.36, 0.41)
36	OK	0.45 (0.42, 0.48)	0.43 (0.41, 0.46)	0.43 (0.41, 0.46)
37	OR	0.56 (0.53, 0.59)	0.56 (0.53, 0.59)	0.56 (0.53, 0.59)
38	PA	0.41 (0.39, 0.44)	0.39 (0.36, 0.42)	0.39 (0.36, 0.42)
39	RI	0.40 (0.37, 0.42)	0.37 (0.35, 0.40)	0.37 (0.34, 0.40)
40	SC	0.45 (0.43, 0.48)	0.42 (0.39, 0.45)	0.42 (0.39, 0.45)
41	SD	0.51 (0.47, 0.56)	0.50 (0.46, 0.55)	0.50 (0.46, 0.55)
42	TN	0.49 (0.46, 0.51)	0.46 (0.43, 0.49)	0.46 (0.43, 0.49)
43	TX	0.47 (0.44, 0.50)	0.45 (0.42, 0.48)	0.45 (0.42, 0.48)
44	UT	0.63 (0.61, 0.66)	0.63 (0.60, 0.66)	0.63 (0.60, 0.66)
45	VT	0.38 (0.35, 0.40)	0.35 (0.33, 0.38)	0.35 (0.33, 0.38)
46	VA	0.46 (0.43, 0.49)	0.43 (0.41, 0.46)	0.43 (0.40, 0.46)
47	WA	0.59 (0.56, 0.62)	0.59 (0.56, 0.62)	0.59 (0.56, 0.62)
48	WV	0.38 (0.36, 0.40)	0.32 (0.30, 0.35)	0.30 (0.27, 0.33)
49	WI	0.40 (0.38, 0.43)	0.37 (0.34, 0.40)	0.37 (0.34, 0.40)
50	WY	0.31 (0.28, 0.33)	0.23 (0.20, 0.26)	0.19 (0.16, 0.23)

is fractionally integrated (Diebold and Rudebusch 1991; Hassler and Wolters 1995; Lee and Schmidt 1996), this being another advantage of the fractional approach used in this article.

To allow for a much richer modeling structure, we also permit deterministic components, and following here

the approach of Bhargava (1986), Schmidt and Phillips (1992), and many others on the specification of unit roots, we permit for a constant and a linear time trend, such that, supposing that y_t is the original data,

$$y_t = \alpha + \beta t + x_t \quad t = 1, 2, \dots, \quad (3)$$

TABLE 6. Estimated coefficients for each series for PM_{2.5}. Confidence limits of d are given in parentheses in the third column, and t statistic estimates for intercept and trend coefficients are given in parentheses in the fourth and fifth columns, respectively.

No.	State	No terms	An intercept	A linear time trend
1	AL	0.35 (0.32, 0.37)	56.8952 (12.96)	−0.003 20 (−1.80)
2	AK	0.48 (0.45, 0.51)	22.8311 (3.06)	—
3	AZ	0.32 (0.30, 0.33)	53.4817 (17.04)	—
4	AR	0.42 (0.40, 0.45)	59.1584 (10.54)	−0.002 64 (−1.77)
5	CA	0.55 (0.52, 0.57)	71.4470 (5.87)	—
6	CO	0.33 (0.30, 0.35)	38.2575 (10.44)	—
7	CT	0.36 (0.34, 0.39)	40.8074 (11.02)	—
8	DE	0.23 (0.21, 0.26)	50.5373 (21.55)	−0.006 10 (−6.58)
9	FL	0.39 (0.36, 0.42)	46.9244 (11.01)	—
10	GA	0.39 (0.37, 0.42)	72.4035 (13.32)	−0.003 60 (−2.70)
11	HI	0.46 (0.44, 0.48)	21.9707 (3.55)	—
12	ID	0.50 (0.48, 0.53)	53.4019 (6.22)	—
13	IL	0.16 (0.13, 0.20)	52.1074 (28.01)	−0.009 20 (−6.92)
14	IN	0.45 (0.42, 0.49)	62.9697 (8.57)	—
15	IA	0.47 (0.44, 0.51)	44.8293 (6.26)	—
16	KS	0.25 (0.22, 0.29)	45.5988 (16.35)	−0.004 27 (−2.76)
17	KY	0.22 (0.19, 0.26)	53.6037 (16.94)	−0.008 00 (−2.27)
18	LA	0.45 (0.42, 0.48)	57.7868 (9.46)	—
19	ME	0.12 (0.05, 0.22)	26.5053 (9.87)	−0.0309 (−1.65)
20	MD	0.41 (0.38, 0.45)	66.1003 (10.56)	−0.004 00 (−2.40)
21	MA	0.32 (0.30, 0.35)	59.6733 (17.32)	−0.002 46 (−3.10)
22	MI	0.17 (0.15, 0.20)	47.2078 (28.09)	−0.004 86 (−6.72)
23	MN	0.10 (−0.06, 0.33)	45.1945 (6.42)	—
24	MS	0.45 (0.42, 0.48)	56.8522 (9.70)	—
25	MO	0.14 (0.08, 0.22)	47.1770 (15.01)	—
26	MT	0.50 (0.48, 0.53)	28.3140 (3.20)	—
27	NE	0.17 (0.14, 0.20)	40.8903 (21.44)	−0.005 50 (−4.20)
28	NV	0.64 (0.60, 0.68)	12.8073 (1.96)	—
29	NH	0.13 (0.10, 0.16)	40.6726 (21.85)	−0.005 20 (−3.15)
30	NJ	0.35 (0.32, 0.37)	66.4176 (13.52)	−0.002 55 (−2.19)
31	NM	0.38 (0.36, 0.40)	17.3624 (9.15)	—
32	NY	0.31 (0.28, 0.33)	45.4411 (12.52)	−0.003 52 (−3.10)
33	NC	0.43 (0.40, 0.46)	52.7887 (8.90)	—
34	ND	0.39 (0.36, 0.42)	33.8361 (7.42)	—
35	OH	0.38 (0.36, 0.41)	63.6265 (12.49)	−0.004 73 (−3.23)
36	OK	0.43 (0.41, 0.46)	43.8001 (7.68)	—
37	OR	0.56 (0.53, 0.59)	43.6885 (4.58)	—
38	PA	0.39 (0.36, 0.42)	55.6072 (8.90)	—
39	RI	0.37 (0.35, 0.40)	44.2762 (11.74)	—
40	SC	0.42 (0.39, 0.45)	56.6492 (10.13)	−0.003 41 (−2.07)
41	SD	0.50 (0.46, 0.55)	15.3274 (2.76)	—
42	TN	0.46 (0.43, 0.49)	64.2001 (10.25)	−0.003 56 (−1.94)
43	TX	0.45 (0.42, 0.48)	43.9724 (7.48)	—
44	UT	0.63 (0.60, 0.66)	57.9306 (4.24)	—
45	VT	0.35 (0.33, 0.38)	44.1075 (9.25)	−0.002 97 (−1.82)
46	VA	0.43 (0.40, 0.46)	56.7748 (9.39)	−0.003 37 (−1.99)
47	WA	0.59 (0.56, 0.62)	74.4716 (7.52)	—
48	WV	0.30 (0.27, 0.33)	65.8890 (18.79)	−0.009 95 (−6.12)
49	WI	0.37 (0.34, 0.40)	50.3533 (9.76)	−0.007 01 (−6.02)
50	WY	0.19 (0.16, 0.23)	26.5719 (21.83)	−0.003 60 (−2.13)

where α and β are unknown coefficients referring, respectively, to the constant and the time trend and x_t is supposed to be given by Eq. (1), that is, following an $I(d)$ process.

The estimation is carried out by using the Whittle function in the frequency domain (see, e.g., Dahlhaus 1989) and we use a version of the tests of Robinson

(1994) that is very convenient in the context of the present data. Thus, we test the null hypothesis:

$$H_o: d = d_o, \quad (4)$$

for any real value d_o , in the model given by Eqs. (3) and (1), reporting the confidence intervals of the

nonrejection values of d_o . The test is based on the Lagrange multiplier principle, and thus it does not require preliminary estimation of d , and, more important, is valid for any real value d , including then, values in the nonstationary range ($d \geq 0.5$). Moreover, the limiting distribution is standard normal, and this limiting behavior is unaffected by the presence of the deterministic terms of the form as in Eq. (3). For further details, see Robinson (1994) or any of its numerous empirical applications (Gil-Alaña and Robinson 1997; Gil-Alana 2005; Abbritti et al. 2016; etc.).

b. Data

The datasets used in this paper are daily outdoor air quality indices, based on fine and coarse particulate matter ($PM_{2.5}$ and PM_{10}), for all 50 U.S. states. These datasets were retrieved from the database of the EPA (<https://www.epa.gov/outdoor-air-quality-data/air-data-multiyear-tile-plot>).

Table 1 presents the data description, with start and end dates for both time series of particulate matter. Most sites have datasets commencing from 1999 and ending in 2019. For those with shorter series length, recorded sample sizes are still long enough for time series analysis. These are the cases of Hawaii, Kentucky, Maine, Minnesota, Missouri, Nevada, and South Dakota states for $PM_{2.5}$, while for PM_{10} , we have the cases of Florida, Illinois, Kentucky, Michigan, Minnesota, Montana, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Oklahoma, Washington, and West Virginia states with time series not commencing from 1999 or ending in 2019. Appendix A (Table A1) gives additional information for the states such as their abbreviations, capital cities, and the total area, land area, and water area. Each capital city area represents the state with the given air pollutant, although in a very few cases other cities' data were reported for the corresponding states because of data unavailability. For example, in $PM_{2.5}$, datasets from Hilo, Baltimore–Colombia–Townson, Albert Lea, Columbia, and Rutland were used to proxy data for Honolulu (Hawaii), Annapolis (Maryland), Saint Paul (Minnesota), Jefferson City (Missouri), and Montpelier (Vermont), respectively. For PM_{10} , datasets from Bowling Green, Philadelphia–Caden–Wilmington, Kingston, urban Honolulu, Battle Creek, Joplin, Sioux City, Elko, Klamath Falls, and Brooking were used to proxy data for Frankfort (Kentucky), Dover (Delaware), Albany (New York), Honolulu (Hawaii), Lansing (Michigan), Columbus (Missouri), Lincoln (Nebraska), Carson City (Nevada), Salem (Oregon), and Pierre (South Dakota), respectively.

TABLE 7. Classification based on significant time trend coefficients.

PM_{10}	Time trend coef	$PM_{2.5}$	Time trend coef
Illinois	0.105 60	West Virginia	−0.009 95
Rhode Island	−0.011 26	Illinois	−0.009 20
Maine	−0.010 20	Kentucky	−0.008 00
Maryland	−0.007 62	Wisconsin	−0.007 01
Arkansas	−0.007 01	Delaware	−0.006 10
Vermont	−0.006 61	Nebraska	−0.005 50
Tennessee	−0.006 46	New Hampshire	−0.005 20
Massachusetts	−0.006 06	Michigan	−0.004 86
Wisconsin	−0.005 28	Ohio	−0.004 73
Virginia	−0.005 00	Kansas	−0.004 27
South Carolina	−0.004 26	Maryland	−0.004 00
Utah	−0.002 59	Georgia	−0.003 60
Louisiana	−0.002 45	Wyoming	−0.003 60
Iowa	−0.002 42	Tennessee	−0.003 56
Indiana	−0.002 37	New York	−0.003 52
Connecticut	−0.002 28	South Carolina	−0.003 41
Missouri	−0.001 63	Virginia	−0.003 37
Delaware	−0.001 16	Alabama	−0.003 20
Georgia	−0.001 08	Maine	−0.003 09
Hawaii	−0.000 95	Vermont	−0.002 97
		Arkansas	−0.002 64
		New Jersey	−0.002 55
		Massachusetts	−0.002 46

As an illustration of the time series, in Fig. 1 we display plots of the air pollution levels by fine and coarse particulate matter ($PM_{2.5}$ and PM_{10}), for only two states: Alabama and Wyoming. The four plots clearly indicate evidence supporting seasonal variation in the distribution of particulate matters over the sample periods.¹

In Table 2, we summarize the data by using mean, minimum, and maximum values for both particulate matters. We found, in most cases $0 \mu\text{g m}^{-3}$ minimum value for both time series of particulate matter ($PM_{2.5}$ and PM_{10}), and the average $PM_{2.5}$ value is above the exceedances limit of $35.4 \mu\text{g m}^{-3}$ for the moderate category of AQI in 38 of 50 states [see appendix B (Table B1)], and the overall time series maximum value is found within unhealthy ranges, implying that U.S. states are at risk of high $PM_{2.5}$. For PM_{10} , $154 \mu\text{g m}^{-3}$ is the limit for the moderate category of AQI, and the value indicates that the average particulate matter level for PM_{10} is still within the moderate limit, even though the minimum and maximum values indicate that there are exceedances in a few cases.

¹ Time plots of $PM_{2.5}$ and PM_{10} for the remaining 48 U.S. states are available on request.

TABLE 8. Classification based on the degree of persistence for PM₁₀.

$d = 0$	$0 < d < 0.5$	$0.5 \leq d < 1$	$0 < d < 1$
Minnesota (0.06)	Vermont (0.10)		Mississippi (0.46)
Michigan (0.09)	Rhode Island (0.16)		Florida (0.47)
	Washington (0.17)		West Virginia (0.47)
	Arkansas (0.19)		Idaho (0.48)
	New Jersey (0.19)		Kentucky (0.48)
	Texas (0.20)		North Dakota (0.49)
	Wisconsin (0.21)		
	Illinois (0.22)		
	Maryland (0.22)		
	Massachusetts (0.22)		
	Virginia (0.22)		
	Alaska (0.23)		
	Maine (0.23)		
	Delaware (0.26)		
	New York (0.26)		
	New Mexico (0.27)		
	Indiana (0.28)		
	Alabama (0.29)		
	Arizona (0.29)		
	Connecticut (0.30)		
	Tennessee (0.30)		
	Iowa (0.31)		
	South Carolina (0.34)		
	South Dakota (0.35)		
	Ohio (0.37)		
	Oklahoma (0.37)		
	Utah (0.37)		
	Georgia (0.38)		
	Wyoming (0.38)		
	Colorado (0.40)		
	Hawaii (0.40)		
	Louisiana (0.40)		
	Oregon (0.43)		
	North Carolina (0.44)		
	California (0.45)		
	Kansas (0.45)		
	Pennsylvania (0.45)		

3. Empirical results and discussion

Having explored the datasets, we conducted the empirical analysis using the fractional integration framework described above. Our estimated empirical model is the one given by Eqs. (1) and (3), that is,

$$y_t = \alpha + \beta t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (5)$$

where y_t is the observed time series and u_t is supposed to be a white-noise process. We could also allow for weak autocorrelation in u_t , although we have preferred to keep all the information on the dependence in the data by means of the differencing parameter d .

Tables 3–6 contain estimated values and coefficients, confidence intervals, and so on for the variables in

Eq. (5). Across Tables 3 and 5, we display the estimated values of d in Eq. (5) jointly with the 95% confidence intervals of the nonrejection values of d using Robinson's (1994) tests, respectively, for the PM₁₀ and PM_{2.5} series. In each case, we consider three potential scenarios: (i) imposing that $\alpha = \beta = 0$ in (5); (ii) imposing $\beta = 0$ in Eq. (5), that is, including only an intercept; and (iii) with α and β freely estimated from the data, that is, including a linear time trend. We have marked in the tables in boldface type the selected specification for each case; this selection is made according to the t values of the estimated coefficients. Tables 4 and 6 display the estimated coefficients for d , α , and β for each series.

We start by presenting the results for PM₁₀ (Tables 3 and 4). The first thing we observe is that the time trend is required in 20 of the 50 cases examined,

TABLE 9. Classification based on the degree of persistence for $PM_{2.5}$.

$d = 0$	$0 < d < 0.5$	$0.5 \leq d < 1$	$0 < d < 1$
Minnesota (0.10)	Maine (0.12)	California (0.55)	Iowa (0.47)
	New Hampshire (0.13)	Oregon (0.56)	Alaska (0.48)
	Missouri (0.14)	Washington (0.59)	Idaho (0.50)
	Illinois (0.16)	Nevada (0.60)	Montana (0.50)
	Michigan (0.17)	Utah (0.63)	South Dakota (0.50)
	Nebraska (0.17)		
	Wyoming (0.19)		
	Kentucky (0.22)		
	Delaware (0.23)		
	Kansas (0.25)		
	West Virginia (0.30)		
	New York (0.31)		
	Massachusetts (0.32)		
	Colorado (0.33)		
	Arizona (0.34)		
	Alabama (0.35)		
	Vermont (0.35)		
	New Jersey (0.35)		
	Connecticut (0.36)		
	Wisconsin (0.37)		
	Rhode Island (0.37)		
	Ohio (0.38)		
	New Mexico (0.38)		
	Florida (0.39)		
	Georgia (0.39)		
	Pennsylvania (0.39)		
	North Dakota (0.39)		
	Maryland (0.41)		
	Arkansas (0.42)		
	South Carolina (0.42)		
	Virginia (0.43)		
	Oklahoma (0.43)		
	North Carolina (0.43)		
	Indiana (0.45)		
	Louisiana (0.45)		
	Mississippi (0.45)		
	Texas (0.45)		
	Hawaii (0.46)		
	Tennessee (0.46)		

being significantly negative in almost all cases implying decreases in the level of particulate matter in these cases.² Focusing now on the estimated values of the differencing parameter d , we notice two states (Minnesota and Michigan) where the hypothesis of short memory (i.e., $d = 0$) cannot be rejected. For the majority of the states, the values of d are in the interval $(0, 0.5)$ implying a stationary long-memory pattern, although in five states (Mississippi, Florida, West Virginia, North Carolina, and Kentucky) the intervals include

both stationary ($d < 0.5$) and nonstationary ($d \geq 0.5$) values.

For $PM_{2.5}$ (Tables 5 and 6), the number of states with significant time trend coefficients is 23, again with a negative value in all cases, the values ranging from -0.00246 (Massachusetts) to -0.00995 (West Virginia). For the values of d , we find a single state (Minnesota) with a short-memory pattern ($d = 0$),³ 39 states with values of d in the range $(0, 0.5)$, and five in the nonstationary mean-reverting range $[0.5, 1)$. In another group of five states, the values of d include stationary and nonstationary cases.

² Illinois is the only state with a significant positive time trend coefficient, although for this state we only have 115 observations corresponding to the year 2000 in which no environmental policies had yet been implemented.

³ For this series, Minnesota $PM_{2.5}$, the number of observations is also very small (76).

FIG. 2. The U.S. states and degrees of persistence for PM_{10} (this map was created with mapchart.net).

Table 7 summarizes the results of the two particulate pollutions in terms of the time trends, and Tables 8 and 9 comprise the results in terms of persistence d for PM_{10} and $PM_{2.5}$, respectively.

We observe in Table 7 that Illinois displays the highest time trend coefficient for PM_{10} and that this state emerges second in the trend coefficient reduction for $PM_{2.5}$ after West Virginia. We observe significant trends in both types of particulate matter in

the following states: Arkansas, Delaware, Georgia, Illinois, Maine, Maryland, Massachusetts, South Carolina, Tennessee, Vermont, Virginia, and Wisconsin. In addition, 8 more states (Connecticut, Hawaii, Indiana, Iowa, Louisiana, Missouri, Rhode Island, and Utah) display a significant trend for PM_{10} and another 11 (Alabama, Kansas, Kentucky, Michigan, Nebraska, New Hampshire, New Jersey, New York, Ohio, West Virginia, and Wyoming) display a significant trend for $PM_{2.5}$. Thus,

FIG. 3. As in Fig. 2, but for $PM_{2.5}$ (this map was created with mapchart.net).

TABLE A1. Information for the 50 U.S. states (source: https://en.wikipedia.org/wiki/List_of_states_and_territories_of_the_United_States; accessed 7 December 2019). Here, “abbrev” indicates the states’ abbreviations/postal codes.

No.	Name	Abbrev	Capital city	Date established	Total area	Land area	Water area
1	Alabama	AL	Montgomery	14 Dec 1819	135 767	131 171	4597
2	Alaska	AK	Juneau	3 Jan 1959	1 723 337	1 477 953	245 384
3	Arizona	AZ	Phoenix	14 Feb 1912	295 234	294 207	1026
4	Arkansas	AR	Little Rock	15 Jun 1836	137 732	134 771	2961
5	California	CA	Sacramento	9 Sep 1850	423 967	403 466	20 501
6	Colorado	CO	Denver	1 Aug 1876	269 601	268 431	1170
7	Connecticut	CT	Hartford	9 Jan 1788	14 357	12 542	1816
8	Delaware	DE	Dover	7 Dec 1787	6446	5047	1399
9	Florida	FL	Tallahassee	3 Mar 1845	170 312	138 887	31 424
10	Georgia	GA	Atlanta	2 Jan 1788	153 910	148 959	4951
11	Hawaii	HI	Honolulu	21 Aug 1959	28 313	16 635	11 678
12	Idaho	ID	Boise	3 Jul 1890	216 443	214 045	2398
13	Illinois	IL	Springfield	3 Dec 1818	149 995	143 793	6202
14	Indiana	IN	Indianapolis	11 Dec 1816	94 326	92 789	1537
15	Iowa	IA	Des Moines	28 Dec 1846	145 746	144 669	1077
16	Kansas	KS	Topeka	29 Jan 1861	213 100	211 754	1346
17	Kentucky	KY	Frankfort	1 Jun 1792	104 656	102 269	2387
18	Louisiana	LA	Baton Rouge	30 Apr 1812	135 659	111 898	23 761
19	Maine	ME	Augusta	15 Mar 1820	91 633	79 883	11 750
20	Maryland	MD	Annapolis	28 Apr 1788	32 131	25 142	6990
21	Massachusetts	MA	Boston	6 Feb 1788	27 336	20 202	7134
22	Michigan	MI	Lansing	26 Jan 1837	250 487	146 435	104 052
23	Minnesota	MN	Saint Paul	11 May 1858	225 163	206 232	18 930
24	Mississippi	MS	Jackson	10 Dec 1817	125 438	121 531	3907
25	Missouri	MO	Jefferson City	10 Aug 1821	180 540	178 040	2501
26	Montana	MT	Helena	8 Nov 1889	380 831	376 962	3869
27	Nebraska	NE	Lincoln	1 Mar 1867	200 330	198 974	1356
28	Nevada	NV	Carson City	31 Oct 1864	286 380	284 332	2048
29	New Hampshire	NH	Concord	21 Jun 1788	24 214	23 187	1027
30	New Jersey	NJ	Trenton	18 Dec 1787	22 591	19 047	3544
31	New Mexico	NM	Santa Fe	6 Jan 1912	314 917	314 161	757
32	New York	NY	Albany	26 Jul 1788	141 297	122 057	19 240
33	North Carolina	NC	Raleigh	21 Nov 1789	139 391	125 920	13 471
34	North Dakota	ND	Bismarck	2 Nov 1889	183 108	178 711	4397
35	Ohio	OH	Columbus	1 Mar 1803	116 098	105 829	10 269
36	Oklahoma	OK	Oklahoma City	16 Nov 1907	181 037	177 660	3377
37	Oregon	OR	Salem	14 Feb 1859	254 799	248 608	6191
38	Pennsylvania	PA	Harrisburg	12 Dec 1787	119 280	115 883	3397
39	Rhode Island	RI	Providence	29 May 1790	4001	2678	1324
40	South Carolina	SC	Columbia	23 May 1788	82 933	77 857	5076
41	South Dakota	SD	Pierre	2 Nov 1889	199 729	196 350	3379
42	Tennessee	TN	Nashville	1 Jun 1796	109 153	106 798	2355
43	Texas	TX	Austin	29 Dec 1845	695 662	676 587	19 075
44	Utah	UT	Salt Lake City	4 Jan 1896	219 882	212 818	7064
45	Vermont	VT	Montpelier	4 Mar 1791	24 906	23 871	1035
46	Virginia	VA	Richmond	25 Jun 1788	110 787	102 279	8508
47	Washington	WA	Olympia	11 Nov 1889	184 661	172 119	12 542
48	West Virginia	WV	Charleston	20 Jun 1863	62 756	62 259	497
49	Wisconsin	WI	Madison	29 May 1848	169 635	140 268	29 367
50	Wyoming	WY	Cheyenne	10 Jul 1890	253 335	251 470	1864

the overall reduction in each state’s $PM_{2.5}$ and PM_{10} levels indicates the effect of different air quality policies put in place by the regulatory body.

Table 8 focuses on the persistence level for PM_{10} . We notice that the values range from the short-memory cases of Minnesota (0.06) and Michigan (0.09) to the

largest degrees of persistence in Idaho (0.48) and North Dakota (0.49). Thus, all the estimates of d are found to be smaller than 0.5 and thus being in the long-memory stationary range (though as earlier mentioned, in some cases, we cannot reject nonstationary values in some states). For $PM_{2.5}$, results in Table 9, the values are

slightly more heterogeneous ranging from 0.10 (Minnesota) to some others in the nonstationary range (California, 0.55; Oregon, 0.56; Washington, 0.59; Nevada, 0.60; and Utah, 0.63). For these five states, we obtain values of d in the nonstationary mean-reverting range, the implication is that there is a long-lasting effect of shocks to pollution; thus even though strong policy action can still be applied, these actions will take long periods to have effects on the quality of air in those five states. The two maps in Fig. 1 (upper for PM_{10} and lower for $PM_{2.5}$) summarize the strong gap between the different kinds of persistence: the states on the West Coast have a higher level of persistence with respect to those on the east, where there is a general decreasing trend. Thus, more effective measures seem to have been adopted in the eastern states and the higher level of persistence observed in the west implies that, in the event of exogenous negative shocks, stronger measures must be adopted to recover the original trends compared to the east (Figs. 2 and 3).

4. Conclusions

In this paper, we have examined air quality in the United States by looking at the statistical properties of the time series corresponding to particulate matter (PM_{10} and $PM_{2.5}$) in the 50 U.S. states. For this purpose, we have used long-memory and fractionally integrated techniques, and the results show significant negative time trend coefficients in a number of cases (19 states in the case of PM_{10} and 23 states in the case of $PM_{2.5}$), implying that, in these states, adequate measures are being adopted to improve the air quality level by reducing the level of particulate matter. Focusing on the long-memory issue with regard to this particulate pollution, we observe a large degree of heterogeneity in the degree of persistence across states, as shown in the map, moving from low degrees of persistence in states such as Minnesota (few data here) to others with high degrees of persistence such as Idaho, South Dakota, and Utah. Meanwhile, since persistence estimates are, in general, within the long-memory mean-reverting range, shocks will have transitory effects and weak policy actions will be required in the case of negative shocks increasing levels of pollution. In the case of $PM_{2.5}$, eight states (Idaho, Montana, South Dakota, California, Oregon, Washington, Nevada, and Utah) have high levels of persistence (with values above 0.5) implying nonstationarity and long-lasting shocks. In these cases, strong policy actions are needed to recover the original level/trends.

Bennett et al. (2019) investigated the effect of a reduction in $PM_{2.5}$ levels between 1999 and 2015 at the

TABLE B1. AQI category definitions for the pollutants $PM_{2.5}$ and PM_{10} .

Category	$PM_{2.5}$ ($\mu\text{g m}^{-3}$)	PM_{10} ($\mu\text{g m}^{-3}$)
Good	≤ 12.0	≤ 54
Moderate	12.1–35.4	55–154
Unhealthy for sensitive groups	35.5–55.4	155–254
Unhealthy	55.5–150.4	255–354
Very unhealthy	150.5–250.4	355–424
Hazardous	≥ 250.5	≥ 425

national and county level, stating that reductions in the particulate matter have lowered mortality rates in most U.S. counties. Thus, in the United States, where long-memory evidence is detected in the time dynamics of $PM_{2.5}$ (even in PM_{10}) in all states, in the event of negative shocks increasing pollution, strong actions should be adopted to accelerate the reduction in the mortality rates. The current paper will continue to serve as a quantitative evidence-based air quality regulation and policy paper, meanwhile, further research may attempt to consider different counties or cities in the United States and elsewhere in the world, paying particular attention to industrialized areas. Besides, aggregated data at national level may also be worth examining, noting that aggregation is a typical argument that has been employed to justify the use of long-memory processes in time series (Robinson 1978; Granger 1980; Altissimo et al. 2009; etc.). In this respect, the use of structural breaks is also worth studying. In fact, many authors have shown the links between fractional integration and breaks, arguing that the former can be a spurious phenomenon caused by the presence of breaks that have not been taken into account (Diebold and Inoue 2001; Granger and Hyung 2004; etc.). Work in all these directions is now in progress.

Acknowledgments. Professor Luis A. Gil-Alana gratefully acknowledges financial support from the MINEIC-AEI-FEDER ECO2017-85503-R project from the Ministerio de Economía, Industria y Competitividad (MINEIC), Agencia Estatal de Investigación (AEI) Spain and Fondo Europeo de Desarrollo Regional (FEDER). Comments from the editor and two reviewers are gratefully acknowledged.

APPENDIX A

Information for the States

Table A1 lists the U.S. states, along with their abbreviations, capital cities, dates of achieving statehood, and the total area, land area, and water area.

APPENDIX B

AQI Category Definitions

Table B1 lists the values that define the various AQI categories for PM_{2.5} and PM₁₀.

REFERENCES

- Abbritti, M., L. A. Gil-Alana, Y. Lovcha, and A. Moreno, 2016: Term structure persistence. *J. Financ. Econ.*, **14**, 331–352, <https://doi.org/10.1093/jfinc/nbv003>.
- Altissimo, F. B., P. Mojon, and P. Zaffaroni, 2009: Can aggregation explain the persistence of inflation? *J. Monet. Econ.*, **56**, 231–241, <https://doi.org/10.1016/j.jmoneco.2008.12.013>.
- Avise, J., J. Chen, B. Lamb, C. Wiedinmyer, A. Guenther, E. Salathé, and C. Mass, 2009: Attribution of projected changes in summertime US ozone and PM_{2.5} concentrations to global changes. *Atmos. Chem. Phys.*, **9**, 1111–1124, <https://doi.org/10.5194/acp-9-1111-2009>.
- Bell, M. L., F. Dominici, L. Ebisu, S. L. Zeger, and J. M. Samet, 2007: Spatial and temporal variation in PM_{2.5} chemical composition in the United States for health effects studies. *Environ. Health Perspect.*, **115**, 989–995, <https://doi.org/10.1289/ehp.9621>.
- Bennett, J. E., and Coauthors, 2019: Particulate matter air pollution and national and county life expectancy loss in the USA: A spatiotemporal analysis. *PLOS Med.*, **16**, e1002856, <https://doi.org/10.1371/journal.pmed.1002856>.
- Beran, J., 1994: *Statistics for Long-Memory Processes*. 1st ed. Chapman and Hall/CRC Press, 315 pp.
- Bhargava, A., 1986: On the theory of testing for unit roots in observed time series. *Rev. Econ. Stud.*, **53**, 369–384, <https://doi.org/10.2307/2297634>.
- Box, G. E. P., G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, 2015: *Time Series Analysis: Forecasting and Control*. 5th ed. John Wiley and Sons, 712 pp.
- Chelani, A., 2009: Statistical persistence analysis of hourly ground level ozone concentrations in Delhi. *Atmos. Res.*, **92**, 244–250, <https://doi.org/10.1016/j.atmosres.2008.12.001>.
- , 2016: Long-memory property in air pollutant concentrations. *Atmos. Res.*, **171**, 1–4, <https://doi.org/10.1016/j.atmosres.2015.12.007>.
- Chen, Z., C. P. Barros, and L. A. Gil-Alana, 2016: The presence of air pollution in four mega-cities in China. *Habitat Int.*, **56**, 103–108, <https://doi.org/10.1016/j.habitatint.2016.05.004>.
- Choi, J., J. Y. Oh, Y. S. Lee, K. H. Min, G. Y. Hur, S. Y. Lee, K. H. Kang, and J. J. Shim, 2018: Harmful impact of air pollution on severe acute exacerbation of chronic obstructive pulmonary disease: Particulate matter is hazardous. *Int. J. Chronic Obstruct. Pulm. Dis.*, **13**, 1053–1059, <https://doi.org/10.2147/COPD.S156617>.
- Chu, S.-H., and J. W. Paisie, 2006: An evaluation of current PM_{2.5} conditions in the US. *Atmos. Environ.*, **40**, 206–211, <https://doi.org/10.1016/j.atmosenv.2005.11.080>.
- Clay, K., and N. Z. Muller, 2019: Recent increases in air pollution: Evidence and implications for mortality. NBER Working Paper 26381, 29 pp., <https://doi.org/10.3386/w26381>.
- Dahlhaus, R., 1989: Efficient parameter estimation for self-similar process. *Ann. Stat.*, **17**, 1749–1766, <https://doi.org/10.1214/aos/1176347393>.
- De Jesus, A. L., M. M. Rahman, M. Mazaheri, H. Thompson, L. D. Knibbs, C. Jeong, and L. Morawska, 2019: Ultrafine particles and PM_{2.5} in the air of cities around the world: Are they representative of each other? *Environ. Int.*, **129**, 118–135, <https://doi.org/10.1016/j.envint.2019.05.021>.
- Di, Q., H. Amini, L. Shi, I. Kloog, R. Silvern, J. Kelly, and J. Schwartz, 2019: An ensemble based model of PM_{2.5} concentration across the contiguous United States with high spatiotemporal resolution. *Environ. Int.*, **130**, 104909, <https://doi.org/10.1016/j.envint.2019.104909>.
- Dickey, D. A., and W. A. Fuller, 1979: Distributions of the estimators for autoregressive time series with a unit root. *J. Amer. Stat. Assoc.*, **74**, 427–481, <https://doi.org/10.2307/2286348>.
- Diebold, F. X., and G. D. Rudebusch, 1991: On the power of Dickey-Fuller test against fractional alternatives. *Econ. Lett.*, **35**, 155–160, [https://doi.org/10.1016/0165-1765\(91\)90163-F](https://doi.org/10.1016/0165-1765(91)90163-F).
- , and A. Inoue, 2001: Long memory and regime switching. *J. Econ.*, **105**, 131–159, [https://doi.org/10.1016/S0304-4076\(01\)00073-2](https://doi.org/10.1016/S0304-4076(01)00073-2).
- Dockery, D. W., C. A. Pope III, X. Xu, J. D. Spengler, J. H. Ware, M. E. Fay, B. G. Ferris Jr., and F. E. Speizer, 1993: An association between air pollution and mortality in six U.S. cities. *N. Engl. J. Med.*, **329**, 1753–1759, <https://doi.org/10.1056/NEJM199312093292401>.
- Elliott, G., T. J. Rothenberg, and J. H. Stock, 1996: Efficient tests for an autoregressive unit root. *Econometrica*, **64**, 813–836, <https://doi.org/10.2307/2171846>.
- EPA, 2011: The benefits and costs of the clean air act 1990 to 2020: EPA report to Congress. U.S. EPA Office of Air and Radiation Office of Policy Rep., 238 pp., https://www.epa.gov/sites/production/files/2015-07/documents/fullreport_rev_a.pdf.
- , 2018: Health and Environmental Effects of Particulate Matter (PM). Accessed 4 January 2020, <https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm>.
- Gil-Alana, L. A., 2005: Statistical modeling of the temperatures in the Northern Hemisphere using fractional integration techniques. *J. Climate*, **18**, 5357–5369, <https://doi.org/10.1175/JCLI3543.1>.
- Gil-Alaña, L. A., and P. M. Robinson, 1997: Testing of unit root and other nonstationary hypotheses in macroeconomic time series. *J. Econ.*, **80**, 241–268, [https://doi.org/10.1016/S0304-4076\(97\)00038-9](https://doi.org/10.1016/S0304-4076(97)00038-9).
- Granger, C. W. J., 1980: Long memory relationships and the aggregation of dynamic models. *J. Econ.*, **14**, 227–238, [https://doi.org/10.1016/0304-4076\(80\)90092-5](https://doi.org/10.1016/0304-4076(80)90092-5).
- , and N. Hyung, 2004: Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *J. Empirical Finance*, **11**, 399–421, <https://doi.org/10.1016/j.jempfin.2003.03.001>.
- Hadley, O. L., 2017: Background PM_{2.5} source apportionment in the remote northwestern United States. *Atmos. Environ.*, **167**, 298–308, <https://doi.org/10.1016/j.atmosenv.2017.08.030>.
- Hassler, U., and J. Wolters, 1995: Long memory inflation rates. International evidence. *J. Bus. Econ. Stat.*, **13**, 37–45.
- Hurst, H., 1951: The long-term storage capacity of reservoirs. *Trans. Amer. Soc. Civ. Eng.*, **116**, 770–799.
- Ji, X., Y. Yao, and X. Long, 2018: What causes PM_{2.5} pollution? Cross-economy empirical analysis from socioeconomic perspective. *Energy Policy*, **119**, 458–472, <https://doi.org/10.1016/j.enpol.2018.04.040>.
- Kantelhardt, J. W., S. A. Zschiegner, E. Koscielny-Bunde, S. Havlin, A. Bunde, and H. E. Stanley, 2002: Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A*, **316**, 87–114, [https://doi.org/10.1016/S0378-4371\(02\)01383-3](https://doi.org/10.1016/S0378-4371(02)01383-3).
- Kwiatkowski, D., P. C. B. Phillips, P. Schmidt, and Y. Shin, 1992: Testing the null hypothesis of stationarity against the alternative

- of a unit root: How sure are we that economic time series have a unit root? *J. Econ.*, **54**, 159–178, [https://doi.org/10.1016/0304-4076\(92\)90104-Y](https://doi.org/10.1016/0304-4076(92)90104-Y).
- Lee, D., and P. Schmidt, 1996: On the power of the KPSS test of stationarity against fractionally integrated alternatives. *J. Econ.*, **73**, 285–302, [https://doi.org/10.1016/0304-4076\(95\)01741-0](https://doi.org/10.1016/0304-4076(95)01741-0).
- Lee, S., W. Lee, D. Kim, E. Kim, W. Myung, S. Kim, and H. Kim, 2019: Short-term PM_{2.5} exposure and emergency hospital admissions for mental disease. *Environ. Res.*, **171**, 313–320, <https://doi.org/10.1016/j.envres.2019.01.036>.
- Li, N., and Coauthors, 2019: A model for estimating the lifelong exposure to PM_{2.5} and NO₂ and the application to population studies. *Environ. Res.*, **178**, 108629, <https://doi.org/10.1016/j.envres.2019.108629>.
- Liao, H., W. T. Chen, and J. H. Seinfeld, 2006: Role of climate change in global predictions of future tropospheric ozone and aerosols. *J. Geophys. Res.*, **111**, D12304, <https://doi.org/10.1029/2005JD006852>.
- Maji, S., S. Ghosh, and S. Ahmed, 2018: Association of air quality with respiratory and cardiovascular morbidity rate in Delhi, India. *Int. J. Environ. Health Res.*, **28**, 471–490, <https://doi.org/10.1080/09603123.2018.1487045>.
- Meraz, M., E. Rodriguez, R. Femat, J. C. Echeverria, and J. Alvarez-Ramirez, 2015: Statistical persistence of air pollutants (O₃, SO₂, NO₂ and PM₁₀) in Mexico City. *Physica A*, **427**, 202–217, <https://doi.org/10.1016/j.physa.2015.02.009>.
- Muller, N. Z., R. Mendelsohn, and W. Nordhaus, 2011: Environmental accounting for pollution in the United States economy. *Amer. Econ. Rev.*, **101**, 1649–1675, <https://doi.org/10.1257/aer.101.5.1649>.
- Nikolopoulos, D., K. Moustris, E. Petraki, D. Koulougliotis, and D. Cantzos, 2019: Fractal and long-memory traces in PM₁₀ time series in Athens, Greece. *Environments*, **6**, 29, <https://doi.org/10.3390/environments6030029>.
- Phillips, P. C. B., and P. Perron, 1988: Testing for a unit root in time series regression. *Biometrika*, **75**, 335–346, <https://doi.org/10.1093/biomet/75.2.335>.
- Pillai, P., S. Babu, and K. Moorthy, 2002: A study of PM, PM₁₀ and PM_{2.5} concentrations at a tropical coastal station. *Atmos. Res.*, **61**, 149–167, [https://doi.org/10.1016/S0169-8095\(01\)00136-3](https://doi.org/10.1016/S0169-8095(01)00136-3).
- Pope, C. A., and Coauthors, 2002: Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA*, **287**, 1132–1141, <https://doi.org/10.1001/jama.287.9.1132>.
- , M. Ezzati, and D. W. Dockery, 2009: Fine-particulate air pollution and life expectancy in the United States. *N. Engl. J. Med.*, **360**, 376–386, <https://doi.org/10.1056/NEJMsa0805646>.
- Pryor, S. C., and R. J. Barthelmie, 1996: PM₁₀ in Canada. *Sci. Total Environ.*, **177**, 57–71, [https://doi.org/10.1016/0048-9697\(95\)04865-0](https://doi.org/10.1016/0048-9697(95)04865-0).
- Pye, H. O. T., H. Liao, S. Wu, L. J. Mickley, D. J. Jacob, D. K. Henze, and J. H. Seinfeld, 2009: Effect of changes in climate and emissions on future sulfate-nitrate-ammonium aerosol levels in the United States. *J. Geophys. Res.*, **114**, D01205, <https://doi.org/10.1029/2008JD010701>.
- Racherla, P. N., and P. J. Adams, 2006: Sensitivity of global tropospheric ozone and fine particulate matter concentrations to climate change. *J. Geophys. Res.*, **111**, D24103, <https://doi.org/10.1029/2005JD006939>.
- Robinson, P. M., 1978: Statistical inference for a random coefficient autoregressive model. *Scand. J. Stat.*, **5**, 163–168.
- , 1994: Efficient tests of nonstationary hypotheses. *J. Amer. Stat. Assoc.*, **89**, 1420–1437, <https://doi.org/10.1080/01621459.1994.10476881>.
- Schmidt, P., and P. C. B. Phillips, 1992: LM tests for a unit root in the presence of deterministic terms. *Oxford Bull. Econ. Stat.*, **54**, 257–287, <https://doi.org/10.1111/j.1468-0084.1992.tb00002.x>.
- Shou, Y., Y. Huang, X. Zhu, C. Liu, Y. Hu, and H. Wang, 2019: A review of the possible associations between ambient PM_{2.5} exposures and the development of Alzheimer's disease. *Ecotoxicol. Environ. Saf.*, **174**, 344–352, <https://doi.org/10.1016/j.ecoenv.2019.02.086>.
- Tagaris, E., K. Manomaiphiboon, K. J. Liao, L. R. Leung, J. H. Woo, S. He, P. Amar, and A. G. Russell, 2007: Impacts of global climate change and emissions on regional ozone and fine particulate matter concentrations over the United States. *J. Geophys. Res.*, **112**, D14312, <https://doi.org/10.1029/2006JD008262>.
- Tai, A. P. K., L. J. Mickley, and D. J. Jacob, 2010: Correlations between fine particulate matter (PM_{2.5}) and meteorological variables in the United States: Implications for the sensitivity of PM_{2.5} to climate change. *Atmos. Environ.*, **44**, 3976–3984, <https://doi.org/10.1016/j.atmosenv.2010.06.060>.
- Thompson, J. R., and J. R. Wilson, 2016: Multifractal detrended fluctuation analysis: Practical applications to financial time series. *Math. Comput. Simul.*, **126**, 63–88, <https://doi.org/10.1016/j.matcom.2016.03.003>.
- Varotsos, C., J. Ondov, and M. Efstathiou, 2005: Scaling properties of air pollution in Athens, Greece and Baltimore, Maryland. *Atmos. Environ.*, **39**, 4041–4047, <https://doi.org/10.1016/j.atmosenv.2005.03.024>.
- Weinmayr, G., M. Pedersen, M. Stafoggia, Z. J. Andersen, C. Galassi, J. Munkenast, and G. Nagel, 2018: Particulate matter air pollution components and incidence of cancers of the stomach and the upper aerodigestive tract in the European Study of Cohorts of Air Pollution Effects (ESCAPE). *Environ. Int.*, **120**, 163–171, <https://doi.org/10.1016/j.envint.2018.07.030>.
- World Health Organization, 2013a: Health Risks of Air Pollution in Europe—HRAPIE project: Recommendations for concentration-response functions for cost-benefit analysis of particulate matter, ozone and nitrogen dioxide. WHO Rep., 60 pp., http://www.euro.who.int/__data/assets/pdf_file/0006/238956/Health_risks_air_pollution_HRAPIE_project.pdf.
- , 2013b: Review of evidence on health aspects of air pollution—REVIHAAP project. WHO Tech. Rep., 309 pp., http://www.euro.who.int/__data/assets/pdf_file/0004/193108/REVIHAAP-Final-technical-report-final-version.pdf.
- Wu, J.-Z., D.-D. Ge, L.-F. Zhou, L.-Y. Hou, Y. Zhou, and Q.-Y. Li, 2018: Effects of particulate matter on allergic respiratory diseases. *Chronic Dis. Transl. Med.*, **4**, 95–102, <https://doi.org/10.1016/j.cdtm.2018.04.001>.
- Xue, Y., W. Pan, W. Z. Lu, and H. D. He, 2015: Multifractal nature of particulate matters (PMs) in Hong Kong urban air. *Sci. Total Environ.*, **532**, 744–751, <https://doi.org/10.1016/j.scitotenv.2015.06.065>.