Long Memory and Time Trends in Particulate Matter Pollution ($PM_{2.5}$ and PM_{10}) in the US States

Luis A. Gil-Alana
Faculty of Economics, University of Navarra, Pamplona, Spain &
Universidad Francisco de Vitoria, Spain

OlaOluwa S. Yaya
Environmental Statistics Unit, Department of Statistics, University of Ibadan, Ibadan, Nigeria
& University of Economics Ho Chi Minh City, Vietnam

Oladapo G. Awolaja
Department of Economics, Babcock University, Ilishan-Remo, Nigeria

Lorenzo Cristofaro
Faculty of Mathematics, University of Turin, Italy

Corresponding author: Prof. Luis A. Gil-Alana
University of Navarra
Faculty of Economics and ICS-NCID
31009 Pamplona
Spain

Email: alana@unav.es

ABSTRACT

This paper focuses on the analysis of the time series behaviour of the air quality in the 50 US states by looking at the statistical properties of the particulate matter (PM_{10} 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.

Keywords: Air pollution; fractional persistence; long memory; particulate matter; United States

JEL Classifications: C22, Q53, Q58

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 percent during the 2016-2018 time period, according to Environmental Protection Agency (EPA) datasets. In a report by the National Bureau of Economic Research (NBER), the worsening of air quality in the US 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 PM_{10} and $PM_{2.5}$, the former is coarse particulate with a particle of diameter 10 micrometres, and the latter is fine particulate with a particle of diameter 2.5 micrometres. 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 (US EPA, 2010; Muller, Mendelsohn, and Nordhaus, 2011). $PM_{2.5}$ is majorly of concern to regulators and public health experts due to its microscopic size which aids easier inhaling and absorption into the bloodstream compared to the coarse type, PM_{10}. 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, and these particles are the main cause of haze in many parts of the US.

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.

Air quality in the US has improved significantly due to policies of the EPA and the World Health Organization (WHO) (Pope, Ezzati and Dockery, 2009). The effort was largely due to the health hazard posed by $PM_{2.5}$ (Dockery, et al., 1993; Pope et al., 2002), while in

2015, about 9 percent of the Americans lived in counties with concentrations of $PM_{2.5}$ above the WHO AQI standard of 10 ug/m^3 and 89 percent lived in counties with concentrations of 5-10 ug/m^3. Thus, further reducing $PM_{2.5}$ will likely lower mortality caused by these health hazards.

Studying the dynamics of values of PM_{10} and $PM_{2.5}$ in the US case informs researchers and policymakers about life expectancy in their respective US 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; WHO, 2013b). Shou et al. (2019) examine exposure to $PM_{2.5}$ and the risk of neurodegenerative diseases. They provide evidence that $PM_{2.5}$ induces neurodegenerative diseases. $PM_{2.5}$ has also been found to induce respiratory problems (Choi et al., 2018; Weinmayr et al., 2018 and Wu et al., 2018). Maji et al., (2018) reveal evidence linking $PM_{2.5}$ to cardiovascular diseases.

Pillai et al. (2002) examine the concentration of $PM_{2.5}$ and PM_{10}. From their results, PM_{10} concentration is lower than limits given by various environmental standards, while $PM_{2.5}$ exceeds the threshold set by the US EPA. There is also seasonal variation in $PM_{2.5}$ 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 (US), even though it passes the WHO threshold. Ji et al. (2018) examine the socioeconomic drivers of $PM_{2.5}$ in 79 developing economies and findings from the study indicate that income, urbanization, and the service sector have a significant impact on $PM_{2.5}$ concentration. There also exists an inverted U relationship between urbanization and $PM_{2.5}$ 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 $PM_{2.5}$ situation using the critical design values (CDV) application. Their findings suggest that California and some areas in the East stand the risk of potential future violation of the annual threshold for $PM_{2.5}$ set by NAAQS. 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 $PM_{2.5}$ in the US. Tai et al. (2010) investigate the response of fine particulate matter ($PM_{2.5}$) to meteorological variables using a multiple linear regression model; the study employs observational data for the period of 1998 to 2008. The concentration of $PM_{2.5}$ and its various components are found to have an association with meteorological variables except for temperature, relative humidity (RH), and wind direction. Evidence reveals that climate change has potential effects on $PM_{2.5}$. 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 the General Circulation Model (GCM)-Chemical Transport Model (CTM) 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 $PM_{2.5}$ in the North-western United States. The study makes use of a matrix factorization model by the US EPA to analyse 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 $PM_{2.5}$ for ten cities located in North America, Europe, Asia, and Australia for over twelve 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 $PM_{2.5}$ across the contiguous United States from 2000 to 2015. Findings show that the $PM_{2.5}$ prediction dataset allows an accurate estimate of the adverse effect of $PM_{2.5}$ 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 Guangzhou and Shenzhen. Meraz et al. (2015) used R/S analysis and found evidence of long range dependence in the air pollutants in Mexico City though 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), Nikolopoulos et al. (2019). Other studies have used other non-parametric methods such as the Detrended Fluctuation Analysis (DFA) (Varotsos et al., 2005) and its generalization, the 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 et al., 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 the 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 anlaysis 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 modelling 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 US 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 modelling (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 if long memory is a feature observed in the particulate matter pollution data in the US and for this purpose we use a parametric approach based on fractional integration methods. Secondly, and based on the previous feature, we investigate if time trends are present in the data and if the time trend coefficient changes according to this long memory feature. Implications of the results obtained are presented in the final part of the manuscript.

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, while Section 4 renders the conclusions and policy recommendations.

2. Materials and Methods

2.1 Statistical method

During the analysis of time series, a crucial issue is to determine if the series is stationary or not. With nonstationary series, a standard approach is to take first differences, that is, if the original series, x_t, is nonstationary 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:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \tag{1}$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is 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 equation (1) can be expressed in terms of its binomial expansion, such that, for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \frac{d(d-1)(d-2)}{6} L^3 \ldots$$

and thus,

$$(1 - L)^d x_t = x_t - d\, x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \frac{d(d-1)(d-2)}{6} x_{t-3} + \ldots. \tag{2}$$

Thus, if d is not an integer, x_t depends on all 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 of a model like (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 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, though with long-lasting effects; d =1 refers to the classical I(1) case and values of d ≥ 1 also imply lack of mean reversion. Thus, by using fractional values for the differencing parameter, we allow for a much richer structure in the dynamic specification of the data. Thus, classical methods based on AR(I)MA models only consider the stationary ARMA case that imposes d = 0 and the nonstationary 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 nonstationarity (i.e. Dickey and Fuller, 1979; Phillips and Perron, 1988; Kwiatkowski et al., 1992; Elliot et al., 1996) have very low power if the true data generating process is fractionally integrated (see, Diebold and Rudebush, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996), this being another advantage of the fractional approach used in this article.

Finally, and to allow for a much richer modelling structure, we also permit deterministic components, and following here the approach of Bharghava (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,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t \qquad t \;=\; 1, 2, ..., \tag{3}$$

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 (1), i.e., 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:

$$H_o: \; d \;=\; d_o, \tag{4}$$

for any real value d_o, in the model given by equations (3) and (1), reporting the confidence intervals of the non-rejection values of d_o. The test is based on the Lagrange Multiplier (LM) principle and thus, it does not require preliminary estimation of d, and more importantly, 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 behaviour is unaffected by the presence of the deterministic terms of the form as in (3). For further details, see Robinson (1994) or any of its numerous empirical applications (Gil-Alana and Robinson, 1997; Gil-Alana, 2005; Abbritti et al., 2016; etc.).

2.2. 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 US states. These datasets were retrieved from the database of the United States Environmental Protection Agency (EPA), on the website: 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, North Dakota, Washington, and West Virginia states with time series not commencing from 1999 nor ending in 2019. In the appendix (Table A), we have names of states and their capital cities with the total area, land, and water area of the states. Each capital city area represents the state with the given air pollutant, while in very few cases, other cities' data were reported for the corresponding states due to data unavailability. For example, in $PM_{2.5}$, Hilo's, Baltimore-Colombia-Townson's, Albert Lea's, Columbia's and Rutland's datasets were used to proxy data for Honolulu (Hawaii State), Annapolis (Maryland State), St Paul (Minnesota State), Jefferson City (Missouri State) and Montpelier (Vermont State), respectively. For PM_{10}, Bowling Green's, Philadelphia-Caden-Wilmington's, Kingston's, Urban Honolulu's, Battle Creek's, Joplins, Sioux City's, Elko's, Klamath Falls' and Brooking's datasets were used to proxy data for Frankfort (Kentucky State), Dover (Delaware State), Albany (New York State), Honolulu (Hawaii State), Lansing (Michigan State), Columbus (Missouri State), Lincoln (Nebraska State), Carson City (Nevada State), Salem (Oregon State) and Pierre (South Dakota State), respectively.

[TABLE 1]

As an illustration of the time series, in Figure 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]

[FIGURE 1 HERE]

In Table 2, we summarize the data by using mean, minimum, and maximum values for both particulate matter. We found, in most cases 0 ug/m^3 minimum value for both time series of particulate matter ($PM_{2.5}$ and PM_{10}), while the average $PM_{2.5}$ value is above the exceedances limit of 35.4ug/m^3 for the moderate category of AQI in 38 out of 50 states (see Appendix Table B), and the overall time series maximum value is found within unhealthy ranges, implying that US states are at the risk of high $PM_{2.5}$. By looking at PM_{10}, 154 ug/m^3 is the limit for the

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

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.

[TABLE 2 HERE]

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 equations (1) and (3), i.e.,

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

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, though we have preferred to keep all the information on the dependence in the data by means of the differencing parameter d.

Across Tables 3 and 5, we display the estimated values of d in equation (5) jointly with the 95% confidence intervals of the non-rejection values of d using Robinson's (1994) tests, respectively for the PM_{10} 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 equation (5), i.e, including only an intercept; and finally, iii) with α and β freely estimated from the data, i.e., including a linear time trend. We have marked in the tables in bold, 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.

[TABLES 3 AND 4 HERE]

We start by presenting the results for PM_{10} (Tables 3 & 4). The first thing we observe is that the time trend is required in 20 out of the 50 cases examined, being significantly negative in almost all cases implying decreases in the level of particulate matter in these cases.[2] Focussing 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, though, in five states (Mississippi, Florida, West Virginia, North Carolina and Kentucky), the intervals include both stationary (d < 0.5) and nonstationary (d ≥ 0.5) values.

[TABLES 5 AND 6 HERE]

For the $PM_{2.5}$ (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.

Table 7 summarizes the results of the two particulate pollutions in terms of the time trends, while 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 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, eight more states (Connecticut, Hawaii, Indiana, Iowa, Louisiana, Missouri, Rhode Island, and Utah) display a significant trend

[2] Illinois is the only state with a significant positive time trend coefficient though 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).

for PM_{10} and another eleven (Alabama, Kansas, Kentucky, Michigan, Nebraska, New Hampshire, New Jersey, New York, Ohio, West Virginia, and Wyoming) for $PM_{2.5}$. Thus, the overall reduction in each state' $PM_{2.5}$ and PM_{10} levels indicate the effect of different air quality policies put in place by the regulatory body.

[TABLES 7 - 9 HERE]

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 non-stationary 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 Figure 1 (upper for PM_{10} and lower for PM_{25}) 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.

[FIGURES 2 - 3 HERE]

4. Conclusions

In this paper, we have examined air quality in the US by looking at the statistical properties of the time series corresponding to particulate matter (PM_{10} and $PM_{2.5}$) in the 50 US 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. Focussing 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 national and county level, stating that reductions in the particulate matter have lowered mortality rates in most US counties. Thus, in the US, 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 US 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

Prof. Luis A. Gil-Alana gratefully acknowledges financial support from MINEIC-AEI-FEDER ECO2017-85503-R project from ‘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

[TABLE A1 HERE]

Appendix B

[TABLE B1 HERE]

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Table 1: Data Description and Sample

No.	Name of State	Abv.	$PM_{2.5}$		PM_{10}	
			Start date	End date	Start date	End date
1	Alabama	AL	06/01/1999	03/12/2019	02/01/1999	26/07/2019
2	Alaska	AK	10/04/1999	05/12/2019	06/01/1999	30/06/2019
3	Arizona	AZ	06/01/1999	05/12/2019	01/01/1999	30/09/2019
4	Arkansas	AR	30/06/1999	05/12/2019	06/01/1999	30/09/2019
5	California	CA	03/01/1999	05/12/2019	01/01/1999	30/09/2019
6	Colorado	CO	01/01/1999	05/12/2019	01/01/1999	01/09/2019
7	Connecticut	CT	09/01/1999	05/12/2019	01/01/1999	30/09/2019
8	Delaware	DE	03/01/1999	05/12/2019	06/01/1999	30/09/2019
9	Florida	FL	03/01/1999	05/12/2019	01/01/1999	30/07/2003
10	Georgia	GA	01/01/1999	05/12/2019	01/01/1999	31/08/2019
11	Hawaii	HI	19/01/2001	05/12/2019	01/01/1999	30/09/2019
12	Idaho	ID	03/01/1999	05/12/2019	01/01/1999	30/06/2019
13	Illinois	IL	07/01/1999	05/12/2019	13/01/1999	26/12/2000
14	Indiana	IN	22/01/1999	05/12/2019	06/01/1999	30/09/2019
15	Iowa	IA	05/02/1999	05/12/2019	04/01/1999	30/09/2019
16	Kansas	KS	27/01/1999	05/12/2019	18/01/1999	30/06/2019
17	Kentucky	KY	30/01/1999	08/11/2011	06/01/1999	31/12/2005
18	Louisiana	LA	01/01/1999	17/11/2019	06/01/1999	31/01/2019
19	Maine	ME	05/06/2015	14/06/2019	06/01/1999	14/06/2019
20	Maryland	MD	12/05/1999	05/12/2019	06/01/1999	26/06/2019
21	Massachusetts	MA	03/01/1999	05/12/2019	06/01/1999	16/07/2019
22	Michigan	MI	15/01/1999	05/12/2019	06/01/1999	26/03/2001
23	Minnesota	MN	08/11/1999	30/06/2001	03/10/1999	27/09/2000
24	Mississippi	MS	14/02/1999	05/12/2019	01/01/1999	31/10/2019
25	Missouri	MO	02/04/2002	28/06/2006	03/01/1999	30/09/2019
26	Montana	MT	09/01/1999	06/12/2019	01/01/1999	26/12/2008
27	Nebraska	NE	03/01/1999	30/09/2019	03/01/1999	30/06/2019
28	Nevada	NV	01/04/2003	06/12/2019	01/01/1999	30/06/2019
29	New Hampshire	NH	06/01/1999	31/12/2014	06/01/1999	28/12/2002
30	New Jersey	NJ	03/01/1999	06/12/2019	06/01/1999	28/03/2011
31	New Mexico	NM	06/01/1999	06/12/2019	02/01/1999	12/04/2015
32	New York	NY	02/07/1999	06/12/2019	06/01/1999	29/03/2005
33	North Carolina	NC	01/01/1999	06/12/2019	06/01/1999	30/09/2019
34	North Dakota	ND	20/02/1999	06/12/2019	07/01/2001	30/09/2019
35	Ohio	OH	01/01/1999	06/12/2019	01/01/1999	30/09/2019
36	Oklahoma	OK	01/04/1999	06/12/2019	01/01/2000	31/10/2019
37	Oregon	OR	01/01/1999	06/12/2019	01/01/1999	31/03/2019
38	Pennsylvania	PA	01/01/1999	06/12/2019	02/08/2000	11/06/2019
39	Rhode Island	RI	03/01/1999	06/12/2019	06/01/1999	30/09/2019
40	South Carolina	SC	03/01/1999	06/12/2019	01/01/1999	30/09/2019
41	South Dakota	SD	01/01/2015	06/12/2019	03/01/1999	30/06/2019
42	Tennessee	TN	01/01/1999	06/12/2019	03/01/1999	13/06/2019
43	Texas	TX	12/03/1999	06/12/2019	21/10/1999	26/06/2019
44	Utah	UT	01/01/1999	06/12/2019	01/01/1999	31/10/2019
45	Vermont	VT	03/01/1999	06/12/2019	06/02/1999	26/06/2019
46	Virginia	VA	27/01/1999	30/09/2019	06/01/1999	05/11/2019
47	Washington	WA	03/01/1999	06/12/2019	06/01/1999	29/04/2006
48	West Virginia	WV	03/01/1999	12/11/2019	06/01/1999	22/12/2015
49	Wisconsin	WI	03/01/1999	06/12/2019	06/01/1999	31/08/2019
50	Wyoming	WY	06/01/1999	06/12/2019	06/01/1999	30/09/2019

Table 2: Data Summary and Category

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

Table 3: Estimated d-coefficients and 95% confidence bands: PM_{10}

No	State	No terms	An intercept	A linear time trend
1	Alabama	0.32 (0.29, 0.35)	**0.29 (0.26, 0.33)**	0.29 (0.26, 0.33)
2	Alaska	0.24 (0.20, 0.28)	**0.23 (0.19, 0.27)**	0.23 (0.19, 0.27)
3	Arizona	0.28 (0.27, 0.30)	**0.29 (0.27, 0.31)**	0.29 (0.27, 0.31)
4	Arkansas	0.31 (0.28, 0.33)	0.23 (0.20, 0.26)	**0.19 (0.16, 0.23)**
5	California	0.45 (0.43, 0.48)	**0.45 (0.42, 0.47)**	0.45 (0.42, 0.47)
6	Colorado	0.41 (0.39, 0.43)	**0.40 (0.38, 0.42)**	0.40 (0.38, 0.43)
7	Connecticut	0.34 (0.31, 0.37)	0.30 (0.27, 0.33)	**0.30 (0.27, 0.33)**
8	Delaware	0.29 (0.27, 0.31)	0.26 (0.24, 0.28)	**0.26 (0.23, 0.28)**
9	Florida	0.49 (0.44, 0.53)	**0.47 (0.42, 0.52)**	0.47 (0.42, 0.52)
10	Georgia	0.40 (0.38, 0.43)	0.38 (0.36, 0.41)	**0.38 (0.36, 0.41)**
11	Hawaii	0.41 (0.39, 0.43)	0.40 (0.38, 0.43)	**0.40 (0.38, 0.43)**
12	Idaho	0.49 (0.46, 0.51)	**0.48 (0.45, 0.50)**	0.48 (0.45, 0.50)
13	Illinois	0.21 (0.10, 0.39)	0.26 (0.15, 0.41)	**0.22 (0.09, 0.40)**
14	Indiana	0.34 (0.31, 0.36)	0.29 (0.26, 0.32)	**0.28 (0.25, 0.31)**
15	Iowa	0.34 (0.32, 0.37)	0.31 (0.29, 0.34)	**0.31 (0.28, 0.34)**
16	Kansas	0.46 (0.44, 0.49)	**0.45 (0.42, 0.48)**	0.45 (0.42, 0.48)
17	Kentucky	0.50 (0.46, 0.55)	**0.48 (0.44, 0.53)**	0.48 (0.44, 0.53)
18	Louisiana	0.43 (0.40, 0.46)	0.40 (0.37, 0.43)	**0.40 (0.37, 0.43)**
19	Maine	0.30 (0.27, 0.34)	0.25 (0.21, 0.29)	**0.23 (0.18, 0.27)**
20	Maryland	0.31 (0.28, 0.34)	0.25 (0.22, 0.28)	**0.22 (0.19, 0.25)**
21	Massachusetts	0.32 (0.31, 0.34)	0.27 (0.25, 0.29)	**0.22 (0.20, 0.25)**
22	Michigan	0.07 (-0.02, 0.29)	**0.09 (-0.04, 0.27)**	0.08 (-0.05, 0.27)
23	Minnesota	0.18 (-0.14, 0.45)	**0.06 (-0.09, 0.26)**	0.07 (-0.08, 0.28)
24	Mississippi	0.47 (0.43, 0.52)	**0.46 (0.41, 0.51)**	0.46 (0.41, 0.51)
25	Missouri	0.25 (0.23, 0.27)	0.22 (0.20, 0.25)	**0.22 (0.19, 0.24)**
26	Montana	0.41 (0.37, 0.44)	**0.40 (0.37, 0.44)**	0.40 (0.37, 0.44)
27	Nebraska	0.40 (0.38, 0.43)	**0.39 (0.36, 0.41)**	0.39 (0.36, 0.41)
28	Nevada	0.44 (0.42, 0.47)	**0.44 (0.41, 0.46)**	0.44 (0.41, 0.46)
29	New Hampshire	0.22 (0.09, 0.34)	**0.15 (0.06, 0.27)**	0.15 (0.05, 0.27)
30	New Jersey	0.23 (0.18, 0.28)	**0.19 (0.14, 0.24)**	0.19 (0.14, 0.24)
31	New Mexico	0.31 (0.27, 0.35)	**0.27 (0.23, 0.32)**	0.27 (0.23, 0.32)
32	New York	0.27 (0.20, 0.34)	**0.26 (0.19, 0.33)**	0.26 (0.19, 0.33)
33	North Carolina	0.46 (0.44, 0.49)	**0.44 (0.42, 0.48)**	0.44 (0.41, 0.48)
34	North Dakota	0.49 (0.46, 0.52)	**0.49 (0.46, 0.51)**	0.48 (0.46, 0.50)
35	Ohio	0.38 (0.35, 0.41)	**0.37 (0.34, 0.40)**	0.37 (0.34, 0.40)
36	Oklahoma	0.39 (0.36, 0.42)	**0.37 (0.33, 0.40)**	0.37 (0.33, 0.40)
37	Oregon	0.45 (0.40, 0.50)	**0.43 (0.38, 0.48)**	0.43 (0.38, 0.48)
38	Pennsylvania	0.47 (0.44, 0.50)	**0.45 (0.42, 0.49)**	0.45 (0.42, 0.49)
39	Rhode Island	0.29 (0.26, 0.32)	0.21 (0.18, 0.24)	**0.16 (0.13, 0.21)**
40	South Carolina	0.40 (0.38, 0.42)	0.36 (0.33, 0.39)	**0.34 (0.31, 0.37)**
41	South Dakota	0.37 (0.35, 0.40)	**0.35 (0.33, 0.38)**	0.35 (0.33, 0.38)
42	Tennessee	0.37 (0.35, 0.40)	0.33 (0.30, 0.35)	**0.30 (0.27, 0.33)**
43	Texas	0.26 (0.22, 0.30)	**0.20 (0.16, 0.24)**	0.20 (0.16, 0.24)
44	Utah	0.40 (0.37, 0.42)	0.38 (0.35, 0.40)	**0.37 (0.35, 0.40)**
45	Vermont	0.22 (0.19, 0.27)	0.15 (0.11, 0.19)	**0.10 (0.06, 0.15)**
46	Virginia	0.31 (0.28, 0.33)	0.22 (0.20, 0.26)	**0.22 (0.20, 0.26)**
47	Washington	0.23 (0.14, 0.32)	**0.17 (0.10, 0.25)**	0.17 (0.10, 0.25)
48	West Virginia	0.49 (0.46, 0.52)	**0.47 (0.44, 0.51)**	0.47 (0.44, 0.51)
49	Wisconsin	0.30 (0.26, 0.33)	0.23 (0.19, 0.27)	**0.21 (0.17, 0.25)**
50	Wyoming	0.39 (0.36, 0.41)	**0.38 (0.35, 0.40)**	0.38 (0.35, 0.40)

Note, confidence limits in parentheses

Table 4: Estimated coefficients for each series: PM_{10}

No	State	No terms	An intercept	A linear time trend
1	Alabama	0.29 (0.26, 0.33)	17.2796 (11.61)	---
2	Alaska	0.23 (0.19, 0.27)	7.8790 (11.57)	---
3	Arizona	0.29 (0.27, 0.31)	70.2758 (6.61)	---
4	Arkansas	0.19 (0.16, 0.23)	26.5720 (21.83)	-0.00701 (-6.02)
5	California	0.45 (0.42, 0.47)	24.3394 (6.59)	---
6	Colorado	0.40 (0.38, 0.42)	20.2032 (11.58)	---
7	Connecticut	0.30 (0.27, 0.33)	19.1985 (9.72)	-0.00228 (-1.81)
8	Delaware	0.26 (0.23, 0.28)	26.5493 (16.18)	-0.00116 (-2.88)
9	Florida	0.47 (0.42, 0.52)	13.0903 (4.96)	---
10	Georgia	0.38 (0.36, 0.41)	23.2157 (9.22)	-0.00108 (-1.66)
11	Hawaii	0.40 (0.38, 0.43)	22.2647 (10.53)	-0.00095 (-1.80)
12	Idaho	0.48 (0.45, 0.50)	28.5326 (6.04)	---
13	Illinois	0.22 (0.09, 0.40)	14.3576 (3.72)	0.10560 (1.90)
14	Indiana	0.28 (0.25, 0.31)	25.7129 (13.71)	-0.00237 (-2.95)
15	Iowa	0.31 (0.28, 0.34)	25.6919 (10.28)	-0.00242 (-2.08)
16	Kansas	0.45 (0.42, 0.48)	20.1905 (6.37)	---
17	Kentucky	0.48 (0.44, 0.53)	15.5667 (5.28)	---
18	Louisiana	0.40 (0.37, 0.43)	28.6425 (9.04)	-0.00245 (-1.75)
19	Maine	0.23 (0.18, 0.27)	20.0008 (10.94)	-0.01020 (-3.97)
20	Maryland	0.22 (0.19, 0.25)	28.4817 (17.34)	-0.00762 (-5.79)
21	Massachusetts	0.22 (0.20, 0.25)	25.0263 (22.77)	-0.00606 (-10.39)
22	Michigan	0.09 (-0.04, 0.27)	22.3934 (13.14)	---
23	Minnesota	0.06 (-0.09, 0.26)	22.1955 (13.27)	---
24	Mississippi	0.46 (0.41, 0.51)	17.4952 (5.25)	---
25	Missouri	0.22 (0.19, 0.24)	30.8592 (14.11)	-0.00163 (-2.95)
26	Montana	0.40 (0.37, 0.44)	17.1230 (5.18)	---
27	Nebraska	0.39 (0.36, 0.41)	19.2983 (6.68)	---
28	Nevada	0.44 (0.41, 0.46)	18.8045 (4.98)	---
29	New Hampshire	0.15 (0.06, 0.27)	13.6835 (11.34)	---
30	New Jersey	0.19 (0.14, 0.24)	19.8264 (15.39)	---
31	New Mexico	0.27 (0.23, 0.32)	11.0846 (12.41)	---
32	New York	0.26 (0.19, 0.33)	9.9455 (6.27)	---
33	North Carolina	0.44 (0.42, 0.48)	17.8403 (7.62)	---
34	North Dakota	0.49 (0.46, 0.51)	12.7550 (3.78)	---
35	Ohio	0.37 (0.34, 0.40)	21.9157 (7.73)	---
36	Oklahoma	0.37 (0.33, 0.40)	21.3063 (8.94)	---
37	Oregon	0.43 (0.38, 0.48)	27.3899 (5.35)	---
38	Pennsylvania	0.45 (0.42, 0.49)	18.9998 (6.74)	---
39	Rhode Island	0.16 (0.13, 0.21)	26.8347 (21.21)	-0.01126 (-6.90)
40	South Carolina	0.34 (0.31, 0.37)	42.0332 (13.48)	-0.00426 (-5.69)
41	South Dakota	0.35 (0.33, 0.38)	18.5579 (7.76)	---
42	Tennessee	0.30 (0.27, 0.33)	25.7787 (13.43)	-0.00646 (-4.43)
43	Texas	0.20 (0.16, 0.24)	19.1547 (20.95)	---
44	Utah	0.37 (0.35, 0.40)	39.1423 (8.63)	-0.00259 (-2.36)
45	Vermont	0.10 (0.06, 0.15)	17.3939 (21.27)	-0.00661 (-5.15)
46	Virginia	0.22 (0.20, 0.26)	19.3022 (17.24)	-0.00500 (-4.79)
47	Washington	0.17 (0.10, 0.25)	13.3469 (14.03)	---
48	West Virginia	0.47 (0.44, 0.51)	16.2894 (5.40)	---
49	Wisconsin	0.21 (0.17, 0.25)	19.4885 (14.56)	-0.00528 (-2.93)
50	Wyoming	0.38 (0.35, 0.40)	12.9041 (7.30)	---

Note, confidence limits of d in parentheses in the 3rd column, and t-statistic estimates for intercept and trend coefficients in parentheses in 4th and 5th columns, respectively.

Table 5: Estimated d-coefficients and 95% confidence bands: $PM_{2.5}$

No	State	No terms	An intercept	A linear time trend
1	Alabama	0.40 (0.37, 0.42)	0.35 (0.32, 0.38)	**0.35 (0.32, 0.37)**
2	Alaska	0.48 (0.45, 0.51)	**0.48 (0.45, 0.51)**	0.48 (0.45, 0.51)
3	Arizona	0.34 (0.32, 0.36)	**0.32 (0.30, 0.33)**	0.31 (0.30, 0.33)
4	Arkansas	0.46 (0.43, 0.48)	0.42 (0.40, 0.45)	**0.42 (0.40, 0.45)**
5	California	0.55 (0.53, 0.55)	**0.55 (0.52, 0.57)**	0.55 (0.52, 0.57)
6	Colorado	0.35 (0.33, 0.37)	**0.33 (0.30, 0.35)**	0.33 (0.30, 0.35)
7	Connecticut	0.39 (0.36, 0.41)	**0.36 (0.34, 0.39)**	0.36 (0.34, 0.39)
8	Delaware	0.31 (0.29, 0.34)	0.26 (0.24, 0.28)	**0.23 (0.21, 0.26)**
9	Florida	0.42 (0.40, 0.45)	**0.39 (0.36, 0.42)**	0.39 (0.36, 0.42)
10	Georgia	0.43 (0.41, 0.46)	0.40 (0.37, 0.42)	**0.39 (0.37, 0.42)**
11	Hawaii	0.46 (0.44, 0.48)	**0.46 (0.44, 0.48)**	0.46 (0.44, 0.48)
12	Idaho	0.51 (0.48, 0.53)	**0.50 (0.48, 0.53)**	0.50 (0.48, 0.53)
13	Illinois	0.28 (0.26, 0.31)	0.20 (0.18, 0.23)	**0.16 (0.13, 0.20)**
14	Indiana	0.48 (0.45, 0.51)	**0.45 (0.42, 0.49)**	0.45 (0.42, 0.49)
15	Iowa	0.49 (0.46, 0.55)	**0.47 (0.44, 0.51)**	0.47 (0.44, 0.50)
16	Kansas	0.32 (0.29, 0.34)	0.26 (0.23, 0.29)	**0.25 (0.22, 0.29)**
17	Kentucky	0.30 (0.28, 0.33)	0.23 (0.20, 0.27)	**0.22 (0.19, 0.26)**
18	Louisiana	0.48 (0.45, 0.50)	**0.45 (0.42, 0.48)**	0.45 (0.42, 0.48)
19	Maine	0.21 (0.11, 0.31)	0.14 (0.06, 0.24)	**0.12 (0.05, 0.22)**
20	Maryland	0.45 (0.42, 0.48)	0.42 (0.39, 0.45)	**0.41 (0.38, 0.45)**
21	Massachusetts	0.37 (0.35, 0.39)	0.33 (0.31, 0.33)	**0.32 (0.30, 0.35)**
22	Michigan	0.27 (0.25, 0.29)	0.20 (0.18, 0.22)	**0.17 (0.15, 0.20)**
23	Minnesota	0.16 (-0.05, 0.44)	**0.10 (-0.06, 0.33)**	0.10 (-0.06, 0.33)
24	Mississippi	0.48 (0.45, 0.51)	**0.45 (0.42, 0.48)**	0.45 (0.42, 0.48)
25	Missouri	0.24 (0.17, 0.32)	**0.14 (0.08, 0.22)**	0.14 (0.08, 0.22)
26	Montana	0.51 (0.48, 0.53)	**0.50 (0.48, 0.53)**	0.50 (0.48, 0.53)
27	Nebraska	0.25 (0.23, 0.28)	0.19 (0.16, 0.22)	**0.17 (0.14, 0.20)**
28	Nevada	0.64 (0.60, 0.68)	**0.64 (0.60, 0.68)**	0.64 (0.60, 0.68)
29	New Hampshire	0.20 (0.17, 0.24)	0.14 (0.11, 0.17)	**0.13 (0.10, 0.16)**
30	New Jersey	0.39 (0.36, 0.41)	0.35 (0.32, 0.38)	**0.35 (0.32, 0.37)**
31	New Mexico	0.40 (0.38, 0.42)	**0.38 (0.36, 0.40)**	0.38 (0.36, 0.40)
32	New York	0.35 (0.33, 0.37)	0.31 (0.29, 0.34)	**0.31 (0.28, 0.33)**
33	North Carolina	0.45 (0.43, 0.48)	**0.43 (0.40, 0.46)**	0.43 (0.40, 0.46)
34	North Dakota	0.40 (0.38, 0.43)	**0.39 (0.36, 0.42)**	0.38 (0.36, 0.41)
35	Ohio	0.43 (0.41, 0.45)	0.39 (0.36, 0.42)	**0.38 (0.36, 0.41)**
36	Oklahoma	0.45 (0.42, 0.48)	**0.43 (0.41, 0.46)**	0.43 (0.41, 0.46)
37	Oregon	0.56 (0.53, 0.59)	**0.56 (0.53, 0.59)**	0.56 (0.53, 0.59)
38	Pennsylvania	0.41 (0.39, 0.44)	**0.39 (0.36, 0.42)**	0.39 (0.36, 0.42)
39	Rhode Island	0.40 (0.37, 0.42)	**0.37 (0.35, 0.40)**	0.37 (0.34, 0.40)
40	South Carolina	0.45 (0.43, 0.48)	0.42 (0.39, 0.45)	**0.42 (0.39, 0.45)**
41	South Dakota	0.51 (0.47, 0.56)	**0.50 (0.46, 0.55)**	0.50 (0.46, 0.55)
42	Tennessee	0.49 (0.46, 0.51)	0.46 (0.43, 0.49)	**0.46 (0.43, 0.49)**
43	Texas	0.47 (0.44, 0.50)	**0.45 (0.42, 0.48)**	0.45 (0.42, 0.48)
44	Utah	0.63 (0.61, 0.66)	**0.63 (0.60, 0.66)**	0.63 (0.60, 0.66)
45	Vermont	0.38 (0.35, 0.40)	0.35 (0.33, 0.38)	**0.35 (0.33, 0.38)**
46	Virginia	0.46 (0.43, 0.49)	0.43 (0.41, 0.46)	**0.43 (0.40, 0.46)**
47	Washington	0.59 (0.56, 0.62)	**0.59 (0.56, 0.62)**	0.59 (0.56, 0.62)
48	West Virginia	0.38 (0.36, 0.40)	0.32 (0.30, 0.35)	**0.30 (0.27, 0.33)**
49	Wisconsin	0.40 (0.38, 0.43)	0.37 (0.34, 0.40)	**0.37 (0.34, 0.40)**
50	Wyoming	0.31 (0.28, 0.33)	0.23 (0.20, 0.26)	**0.19 (0.16, 0.23)**

Note, confidence limits in parentheses

Table 6: Estimated coefficients for each series: $PM_{2.5}$

No	State	No terms	An intercept	A linear time trend
1	Alabama	0.35 (0.32, 0.37)	56.8952 (12.96)	-0.00320 (-1.80)
2	Alaska	0.48 (0.45, 0.51)	22.8311 (3.06)	---
3	Arizona	0.32 (0.30, 0.33)	53.4817 (17.04)	---
4	Arkansas	0.42 (0.40, 0.45)	59.1584 (10.54)	-0.00264 (-1.77)
5	California	0.55 (0.52, 0.57)	71.4470 (5.87)	---
6	Colorado	0.33 (0.30, 0.35)	38.2575 (10.44)	---
7	Connecticut	0.36 (0.34, 0.39)	40.8074 (11.02)	---
8	Delaware	0.23 (0.21, 0.26)	50.5373 (21.55)	-0.00610 (-6.58)
9	Florida	0.39 (0.36, 0.42)	46.9244 (11.01)	---
10	Georgia	0.39 (0.37, 0.42)	72.4035 (13.32)	-0.00360 (-2.70)
11	Hawaii	0.46 (0.44, 0.48)	21.9707 (3.55)	---
12	Idaho	0.50 (0.48, 0.53)	53.4019 (6.22)	---
13	Illinois	0.16 (0.13, 0.20)	52.1074 (28.01)	-0.00920 (-6.92)
14	Indiana	0.45 (0.42, 0.49)	62.9697 (8.57)	---
15	Iowa	0.47 (0.44, 0.51)	44.8293 (6.26)	---
16	Kansas	0.25 (0.22, 0.29)	45.5988 (16.35)	-0.00427 (-2.76)
17	Kentucky	0.22 (0.19, 0.26)	53.6037 (16.94)	-0.00800 (-2.27)
18	Louisiana	0.45 (0.42, 0.48)	57.7868 (9.46)	---
19	Maine	0.12 (0.05, 0.22)	26.5053 (9.87)	-0.0309 (-1.65)
20	Maryland	0.41 (0.38, 0.45)	66.1003 (10.56)	-0.00400 (-2.40)
21	Massachusetts	0.32 (0.30, 0.35)	59.6733 (17.32)	-0.00246 (-3.10)
22	Michigan	0.17 (0.15, 0.20)	47.2078 (28.09)	-0.00486 (-6.72)
23	Minnesota	0.10 (-0.06, 0.33)	45.1945 (6.42)	---
24	Mississippi	0.45 (0.42, 0.48)	56.8522 (9.70)	---
25	Missouri	0.14 (0.08, 0.22)	47.1770 (15.01)	---
26	Montana	0.50 (0.48, 0.53)	28,3140 (3.20)	---
27	Nebraska	0.17 (0.14, 0.20)	40.8903 (21.44)	-0.00550 (-4.20)
28	Nevada	0.64 (0.60, 0.68)	12.8073 (1.96)	---
29	New Hampshire	0.13 (0.10, 0.16)	40.6726 (21.85)	-0.00520 (-3.15)
30	New Jersey	0.35 (0.32, 0.37)	66.4176 (13.52)	-0.00255 (-2.19)
31	New Mexico	0.38 (0.36, 0.40)	17.3624 (9.15)	---
32	New York	0.31 (0.28, 0.33)	45.4411 (12.52)	-0.00352 (-3.10)
33	North Carolina	0.43 (0.40, 0.46)	52.7887 (8.90)	---
34	North Dakota	0.39 (0.36, 0.42)	33.8361 (7.42)	---
35	Ohio	0.38 (0.36, 0.41)	63.6265 (12.49)	-0.00473 (-3.23)
36	Oklahoma	0.43 (0.41, 0.46)	43.8001 (7.68)	---
37	Oregon	0.56 (0.53, 0.59)	43.6885 (4.58)	---
38	Pennsylvania	0.39 (0.36, 0.42)	55.6072 (8.90)	---
39	Rhode Island	0.37 (0.35, 0.40)	44.2762 (11.74)	---
40	South Carolina	0.42 (0.39, 0.45)	56.6492 (10.13)	-0.00341 (-2.07)
41	South Dakota	0.50 (0.46, 0.55)	15.3274 (2.76)	---
42	Tennessee	0.46 (0.43, 0.49)	64.2001 (10.25)	-0.00356 (-1.94)
43	Texas	0.45 (0.42, 0.48)	43.9724 (7.48)	---
44	Utah	0.63 (0.60, 0.66)	57.9306 (4.24)	---
45	Vermont	0.35 (0.33, 0.38)	44.1075 (9.25)	-0.00297 (-1.82)
46	Virginia	0.43 (0.40, 0.46)	56.7748 (9.39)	-0.00337 (-1.99)
47	Washington	0.59 (0.56, 0.62)	74.4716 (7.52)	---
48	West Virginia	0.30 (0.27, 0.33)	65.8890 (18.79)	-0.00995 (-6.12)
49	Wisconsin	0.37 (0.34, 0.40)	50.3533 (9.76)	-0.00701 (-6.02)
50	Wyoming	0.19 (0.16, 0.23)	26.5719 (21.83)	-0.00360 (-2.13)

Note, confidence limits of d in parentheses in the 3rd column, and t-statistic estimates for intercept and trend coefficients in parentheses in 4th and 5th columns, respectively.

Table 7: Classification based on the time trend coefficients

Significant time trend coefficients			
PM_{10}	**Time trend coeff.**	**$PM_{2.5}$**	**Time trend coeff.**
Illinois	0.10560	West Virginia	-0.00995
Rhode Island	-0.01126	Illinois	-0.00920
Maine	-0.01020	Kentucky	-0.00800
Maryland	-0.00762	Wisconsin	-0.00701
Arkansas	-0.00701	Delaware	-0.00610
Vermont	-0.00661	Nebraska	-0.00550
Tennessee	-0.00646	New Hampshire	-0.00520
Massachusetts	-0.00606	Michigan	-0.00486
Wisconsin	-0.00528	Ohio	-0.00473
Virginia	-0.00500	Kansas	-0.00427
South Carolina	-0.00426	Maryland	-0.00400
Utah	-0.00259	Georgia	-0.00360
Louisiana	-0.00245	Wyoming	-0.00360
Iowa	-0.00242	Tennessee	-0.00356
Indiana	-0.00237	New York	-0.00352
Connecticut	-0.00228	South Carolina	-0.00341
Missouri	-0.00163	Virginia	-0.00337
Delaware	-0.00116	Alabama	-0.00320
Georgia	-0.00108	**Maine**	**-0.00309**
Hawaii	-0.00095	Vermont	-0.00297
		Arkansas	-0.00264
		New Jersey	-0.00255
		Massachusetts	-0.00246

Table 8: Classification based on the degree of persistence: PM_{10}

d = 0	**0 < d < 0.5**	**0.5 ≤ d < 1**
Minnesota (0.06) Michigan (0.09)	Vermont (0.10) Rhode Island (0.16) Washington (0.17) Arkansas (0.19) New Jersey (0.19) Texas (0.20) 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)	
	0 < d < 1	
	Mississippi (0.46) Florida (0.47) West Virginia (0.47) Idaho (0.48) Kentucky (0.48) North Dakota (0.49)	

Table 9: Classification based on the degree of persistence: $PM_{2.5}$

d = 0	0 < d < 0.5	0.5 ≤ d < 1
Minnesota (0.10)	Mayne (0.12) New Hampshire (0.13) Missouri (0.14) Illinois (0.16) Michigan (0.17) 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) Hawii (0.46) Tennessee (0.46)	California (0.55) Oregon (0.56) Washington (0.59) Nevada (0.60) Utah (0.63)
	0 < d < 1	
	Iowa (0.47) Alaska (0.48) Idaho (0.50) Montana (0.50) South Dakota (0.50)	

APPENDIX A: Table A1: US States

No	Name of State	Abbv.	Capital Cities	Estab. Dates	Total a.	Land a.	Water a.
1	Alabama	AL	Montgomery	Dec 14, 1819	135767	131171	4597
2	Alaska	AK	Juneau	Jan 3, 1959	1723337	1477953	245384
3	Arizona	AZ	Phoenix	Feb 14, 1912	295234	294207	1026
4	Arkansas	AR	Little Rock	Jun 15, 1836	137732	134771	2961
5	California	CA	Sacramento	Sep 9, 1850	423967	403466	20501
6	Colorado	CO	Denver	Aug 1, 1876	269601	268431	1170
7	Connecticut	CT	Hartford	Jan 9, 1788	14357	12542	1816
8	Delaware	DE	Dover	Dec 7, 1787	6446	5047	1399
9	Florida	FL	Tallahassee	Mar 3, 1845	170312	138887	31424
10	Georgia	GA	Atlanta	Jan 2, 1788	153910	148959	4951
11	Hawaii	HI	Honolulu	Aug 21, 1959	28313	16635	11678
12	Idaho	ID	Boise	Jul 3, 1890	216443	214045	2398
13	Illinois	IL	Springfield	Dec 3, 1818	149995	143793	6202
14	Indiana	IN	Indianapolis	Dec 11, 1816	94326	92789	1537
15	Iowa	IA	Des Moines	Dec 28, 1846	145746	144669	1077
16	Kansas	KS	Topeka	Jan 29, 1861	213100	211754	1346
17	Kentucky	KY	Frankfort	Jun 1, 1792	104656	102269	2387
18	Louisiana	LA	Baton Rouge	Apr 30, 1812	135659	111898	23761
19	Maine	ME	Augusta	Mar 15, 1820	91633	79883	11750
20	Maryland	MD	Annapolis	Apr 28, 1788	32131	25142	6990
21	Massachusetts	MA	Boston	Feb 6, 1788	27336	20202	7134
22	Michigan	MI	Lansing	Jan 26, 1837	250487	146435	104052
23	Minnesota	MN	St. Paul	May 11, 1858	225163	206232	18930
24	Mississippi	MS	Jackson	Dec 10, 1817	125438	121531	3907
25	Missouri	MO	Jefferson City	Aug 10, 1821	180540	178040	2501
26	Montana	MT	Helena	Nov 8, 1889	380831	376962	3869
27	Nebraska	NE	Lincoln	Mar 1, 1867	200330	198974	1356
28	Nevada	NV	Carson City	Oct 31, 1864	286380	284332	2048
29	New Hampshire	NH	Concord	Jun 21, 1788	24214	23187	1027
30	New Jersey	NJ	Trenton	Dec 18, 1787	22591	19047	3544
31	New Mexico	NM	Santa Fe	Jan 6, 1912	314917	314161	757
32	New York	NY	Albany	Jul 26, 1788	141297	122057	19240
33	North Carolina	NC	Raleigh	Nov 21, 1789	139391	125920	13471
34	North Dakota	ND	Bismarck	Nov 2, 1889	183108	178711	4397
35	Ohio	OH	Columbus	Mar 1, 1803	116098	105829	10269
36	Oklahoma	OK	Oklahoma City	Nov 16, 1907	181037	177660	3377
37	Oregon	OR	Salem	Feb 14, 1859	254799	248608	6191
38	Pennsylvania	PA	Harrisburg	Dec 12, 1787	119280	115883	3397
39	Rhode Island	RI	Providence	May 29, 1790	4001	2678	1324
40	South Carolina	SC	Columbia	May 23, 1788	82933	77857	5076
41	South Dakota	SD	Pierre	Nov 2, 1889	199729	196350	3379
42	Tennessee	TN	Nashville	Jun 1, 1796	109153	106798	2355
43	Texas	TX	Austin	Dec 29, 1845	695662	676587	19075
44	Utah	UT	Salt Lake City	Jan 4, 1896	219882	212818	7064
45	Vermont	VT	Montpelier	Mar 4, 1791	24906	23871	1035
46	Virginia[E]	VA	Richmond	Jun 25, 1788	110787	102279	8508
47	Washington	WA	Olympia	Nov 11, 1889	184661	172119	12542
48	West Virginia	WV	Charleston	Jun 20, 1863	62756	62259	497
49	Wisconsin	WI	Madison	May 29, 1848	169635	140268	29367
50	Wyoming	WY	Cheyenne	Jul 10, 1890	253335	251470	1864

Source: *https://en.wikipedia.org/wiki/List_of_states_and_territories_of_the_United_States#cite_note-11*. *Retrieved on 07 December 2019.*

APPENDIX B: Table B1: Air Quality Index (AQI) Category for $PM_{2.5}$ and PM_{10}

	Pollutants	
Category	**$PM_{2.5}$ (ug/m^3)**	**PM_{10} (ug/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

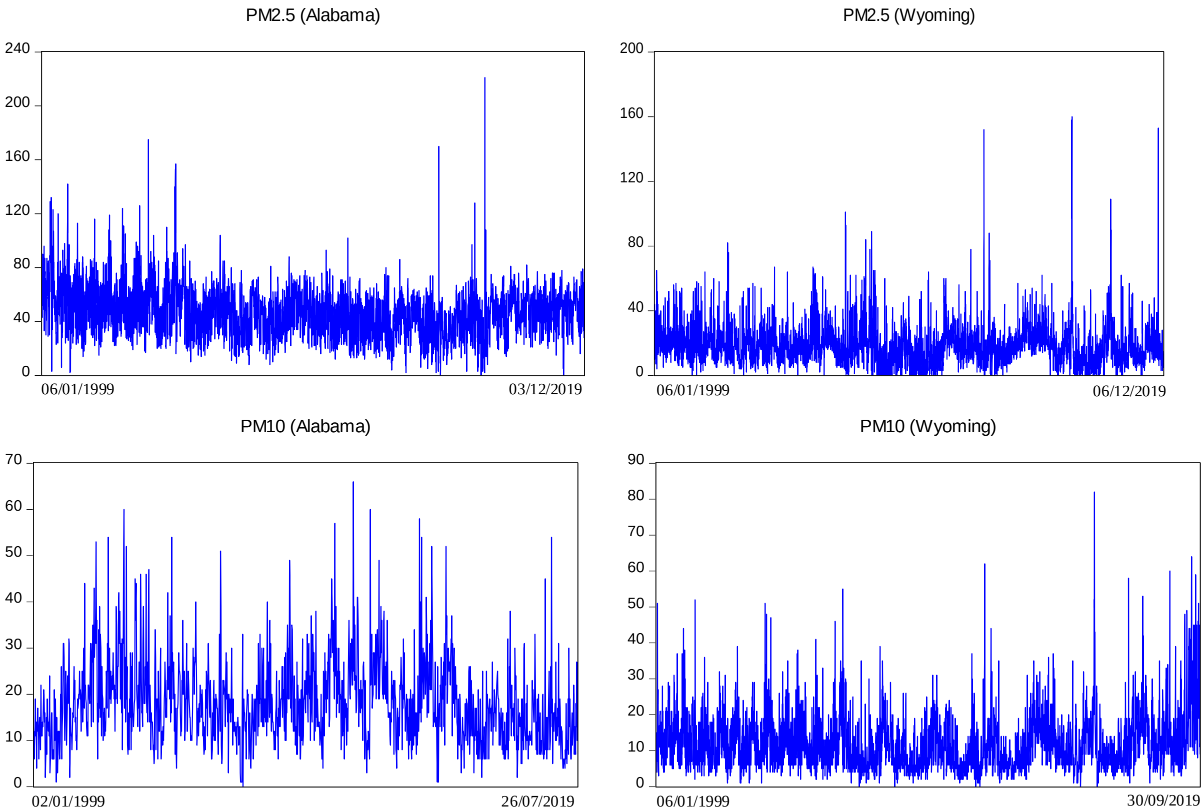

Figure 1: Time plots of fine and coarse particulate matter ($PM_{2.5}$ and PM_{10}) for only Alabama and Wyoming (Other 48 US states cannot be represented due to space)

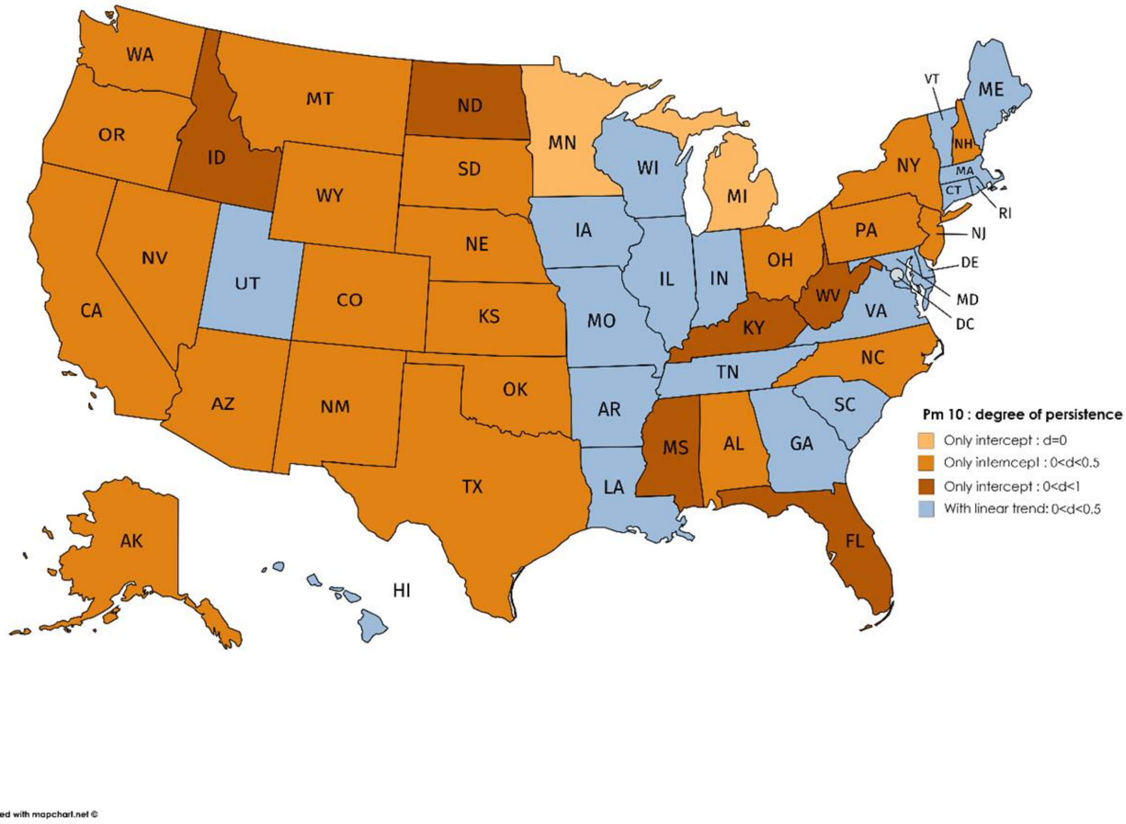

Figure 2: US states and degrees of persistence: PM_{10}

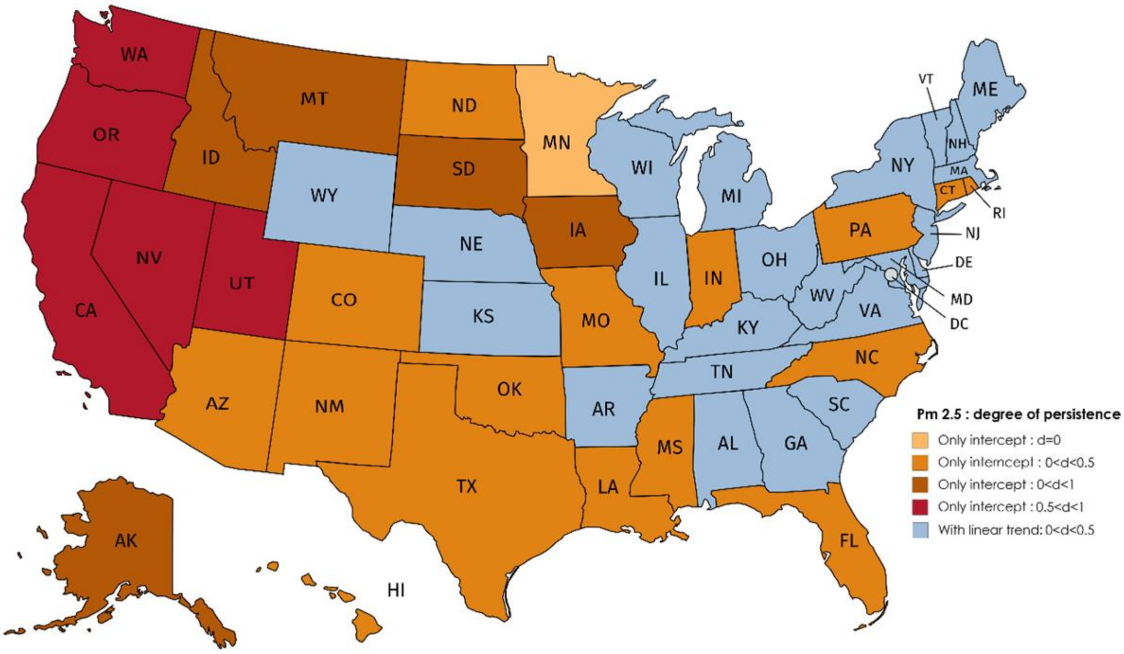

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Figure 3: US states and degrees of persistence: $PM_{2.5}$