Department of Economics and Finance

Working Paper No. 2507

Economics and Finance Working Paper Series

Guglielmo Maria Caporale, Nieves Carmona-González, Luis Alberiko Gil-Alana, and María Fátima Romero Rojo

Air Pollution in 88 US Metropolitan Areas

April 2025

https://www.brunel.ac.uk/economics-and-finance/research-and-phd-programmes/research-papers

Air Pollution in 88 US Metropolitan Areas:

Trends and Persistence

Guglielmo Maria Caporale, Brunel University of London, London, UK

Nieves Carmona-González, Universidad Francisco de Vitoria,

Pozuelo de Alarcón, Madrid, Spain

Luis Alberiko Gil-Alana, University of Navarra, Faculty of Economics,

and NCID, Pamplona, Spain,

and Universidad Francisco de Vitoria, Pozuelo de Alarcón, Madrid, Spain

María Fátima Romero Rojo, Universidad Francisco de Vitoria,

Pozuelo de Alarcón, Madrid, Spain

April 2025

Abstract

This paper analyses trends and persistence in air pollution levels in 88 US metropolitan areas using fractional integration methods. The results indicate that the differencing parameter d is higher than 0 in 38 of the series, which supports the hypothesis of long-memory behaviour and implies that, although the effects of shocks are long-lived, they eventually die out. The highest degrees of persistence are found in the Fresno, Bakersfield, Bradenton and San Diego areas. On the whole the gathered evidence indicates that regional differences in pollution levels are significant, with factors such as industrialisation history and extreme weather events playing a crucial role in their degree of persistence. This suggests that, in order to tackle pollution more effectively, federal environmental policies, such as the Clean Air Act, should be complemented by more targeted ones taking into account local characteristics.

JEL Classification: C22, Q53

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics, Finance and Accounting, Brunel University of London, Uxbridge, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk; https://orcid.org/0000-0002-0144-4135

Luis A. Gil-Alana gratefully acknowledges financial support from the project from 'Ministerio de Ciencia, Innovación y Universidades`Agencia Estatal de Investigación' (AEI) Spain and `Fondo Europeo de Desarrollo Regional' (FEDER), Grant D2023-149516NB-I00 funded by MCIN/AEI/ 10.13039/501100011033, and from an internal Project of the Universidad Francisco de Vitoria.

1. Introduction

Environmental pollution is one of the most pressing challenges faced by mankind owing to its severe consequences for human health, ecosystems and sustainable development. It has become a major concern in the US, especially in the case of the most populated urban areas. The Environmental Protection Agency (EPA) estimates that, in 2022, about 60% of the US population was exposed to hazardous levels of pollution in some form (EPA, 2024a). In response to this threat the US government introduced the Clean Air Act which sets national standards for air quality and has provided a framework for reducing pollutants such as sulphur dioxide and particulate matter (EPA, 2024b).

Understanding how pollution levels have evolved over time is crucial to evaluate the effectiveness of environmental policies and to develop future strategies to respond to the increasing challenges posed by climate change. For this purpose the present study examines pollution trends in 88 US metropolitan areas over the period 1980-2023 using fractional integration techniques. This statistical approach is most suitable for time series with long-memory properties and persistent dynamics that cannot be adequately modelled using traditional methods. In particular, the main advantage of the fractional integration approach (Granger and Joyeux, 1980) is that it allows the differencing parameter d to be any real number, including fractional ones, and thus captures more accurately both long- and short-term correlations (Huang et al., 2022,). Moreover, it yields efficient estimates and more robust results (Bhardwaj et al., 2020; Ismail et. al. 2023).

The analysis in this paper provides new, comprehensive evidence on the stochastic properties of pollution in the 88 US metropolitan areas considered, specifically on the possible presence of trends and on the degree of persistence of the series under investigation. Such information is essential to design more targeted and effective policies to reduce pollution and mitigate its adverse effects.

The layout of the paper is the following: Section 2 briefly reviews the relevant literature; Section 3 describes the data; Section 4 outlines the econometric framework based on the concept of fractional integration; Section 5 presents the empirical results; Section 6 offers some concluding remarks.

2. Literature Review

There exists an extensive literature on air pollution in the US and its adverse effects on public health, numerous papers identifying various diseases and chronic conditions that are strongly associated with continued exposure to high levels of air pollutants. Such studies have addressed both the immediate consequences and the long-term health effects of pollution, especially on vulnerable groups including children, the elderly, and low-income communities (Barrett et al., 2015; Bevan et al., 2021; Malik et al., 2022; Remigio et al., 2022; Liu, 2023; Pokharel et al., 2023; Ni et al., 2024; Maji et al., 2024, among others). In addition to health effects, the economic costs of air pollution in the US have also been analysed in depth – these include direct and indirect expenses related to medical care, loss of labour productivity, and the impact on sectors such as agriculture and tourism (Hsiang et al., 2017; Cropper et al., 2019; Pandey et al., 2021; Smith, 2023). This evidence shows not only the magnitude of the environmental problem, but also its social and economic impact.

Environmental inequality in the US is another central theme in pollution studies. Low-income communities, particularly those located in highly industrialised urban areas, are disproportionately affected by air pollution, which contributes to greater inequality in terms of health, access to quality services, and living conditions (Rubio et al., 2022; Bradley et al., 2024). Studies on this topic highlight the urgent need for reducing social and environmental disparities through inclusive policies and a comprehensive approach to improving the quality of life of all citizens.

The cumulative effects of historical factors, seasonal variations, and regulatory interventions have resulted in highly complex patterns of behaviour in US pollution levels. This country is responsible for approximately 25% of historical global CO_2 emissions (Hannah et al., 2019). In fact, US greenhouse gas emissions account for 79.7% of global ones (EPA, 2024a), which implies that the US has a key role in mitigating the effects of climate change by implementing effective policies to reduce pollutant emissions and improve air quality. Climate change and pollution are problems that cannot be addressed in isolation; an integrated approach is needed to achieve a healthier and more sustainable future.

The present study contributes to a specific branch of the literature modelling atmospheric pollution series by means of fractional integration techniques. This approach, relatively new in environmental analysis, is ideal for analysing time series, such as air pollutant concentrations, with long-memory properties and persistent patterns driven by a range of historical and seasonal factors. The usefulness of this framework for modelling pollution series with long-term dependence has been shown in various recent studies (Yuan et al., 2019; Gil-Alana et al., 2020a,b; Yaya et al., 2020; Sakiru et al., 2021; Gil-Alana and Lenti, 2021; Sakiru et al., 2021; Gil-Alana and Lenti, 2021; Caporale et al., 2021, 2024, among others); the long memory detected in many pollution time series indicates that present pollution levels have a significant influence on future ones, which makes monitoring and early intervention to mitigate their effects extremely important.

However, other studies using this approach find that pollution may be absorbed by natural systems and that changes in environmental policies or interventions may affect its long-run trends. For instance, Caporale et al. (2021) reported mean reversion in PM_{10}

concentrations in eight European capitals from 2014 to 2020, which implies that the effects of environmental shocks on those series are not permanent, but tend to be corrected over time. Similarly, Bermejo et al. (2022) concluded that mean reversion occurs in $PM_{2.5}$ concentrations in 20 global megacities between 2018 and 2020, and thus that shocks have transient effects.

In another study, Gil-Alana et al. (2018) examined global and per capita Nitrogen Oxides (NO_x) and volatile organic compounds (VOC) emissions in the US from 1914 to 2014 and also the effectiveness of environmental policies; they found that by 2014 the US had managed to reduce both VOC and NO_x per capita emission levels compared to 1970. Instead Gil-Alana et al. (2020a) carried out a detailed analysis of air quality in London, and obtained evidence of persistent behaviour in the seven pollutants examined. In two additional studies, Gil-Alana et al. (2019) investigated the time evolution of CO_2 emissions in the European Union, while Gil-Alana et al. (2020b) examined air quality in the 50 US states, focusing on PM_{10} and $PM_{2.5}$ pollutants, and concluded that shocks and policy actions have long-lived effects at both the local and national levels. Finally, other research has focused on the convergence of pollutant series in US regions (Payne et al., 2014; Apergis et al., 2017). All these studies indicate that long memory and persistence are two important properties of pollutants in the US.

3. Data Description

The series used for the analysis provide information about air quality in 88 US metropolitan areas by measuring the number of days between 1980 and 2023 when the Air Quality Index (AQI) exceeded a threshold of 100. Such a value indicates poor air quality (i.e., within the unhealthy range), and that on the day in question at least one of the pollutants exceeded the level consistent with the set air quality standards (EPA, 2024c). In particular, the Air Quality Index (AQI) incorporates information about six major pollutants (PM_{10}, $PM_{2.5}$, sulphur dioxide, carbon monoxide, ozone, and nitrogen dioxide) across an entire monitoring network to produce a single number that represents the worst daily air quality experienced in an urban area (Plaia and Ruggieri, 2011). Note that historical AQI data are at times revised. The main reason is that changes to the National Ambient Air Quality Standards (NAAQS) are applied retroactively to data from previous years to provide consistent comparisons over time. This information is compiled by the Environmental Protection Agency (EPA) and is updated regularly as air quality standards change.

The data have been retrieved from the database of the Bureau of Transportation Statistics, United States Department of Transportation, available at: https://www.bts.gov/content/air-pollution-trends-selected-metropolitan-statistical-areas. The data source is: U.S. Environmental Protection Agency, Office of Air and Radiation, Air Trends, Air Quality Index: Daily AQI, available at https://aqs.epa.gov/aqsweb/airdata/download_files.html as of Dec. 11, 2024.

Table 1 and Figure 1 display some descriptive statistics of the series for the 88 US metropolitan areas considered, such as the maximum and minimum value, the mean and the standard deviation of the number of days exceeding 100 in the AQI between1980 and 2023. It can be seen that seven of the areas considered have more than 200 poor air quality days in a year, namely: Bakersfield, CA; Bridgeport-Stamford-Norwalk, CT; Fresno, CA; Phoenix-Mesa-Scottsdale, AZ; Riverside-San Bernardino-Ontario, CA; San Diego-Carlsbad, CA. In particular, the highest value is observed in the case of Los Angeles-Long Beach-Anaheim, CA, with a record 287 days in 1980. However, the number of unhealthy air quality days in this area has been decreasing almost every year, reaching 87 in 2023, which results in a mean value of 157.14 days with a standard deviation of 54.14.

By contrast, McAllen-Edinburg-Mission, TX exhibits the lowest number of poor air quality days, with an AQI higher than 100 for 9 days in 2003, and equal to 0 in 16 of the 43 years within the sample period, with a mean value of only 2.07 days and a standard deviation of 2.73.

[TABLE 1 AND FIGURE 1 ABOUT HERE]

4. Modelling Framework

Long memory is a widely observed feature in hydrological and climatological data (including air pollution ones, as previously mentioned). In such a case the spectral density function of a stationary process has one or more poles or singularities in the spectrum, which in environmental series often corresponds to the zero frequency. This is normally interpreted as implying that the series should be first-differenced (Granger, 1966, 1980); however, the spectrum of the first-differenced data is often close to zero at the zero frequency, which suggests that over-differentiation has occurred. This finding motivates the fractional integration approach, which is suitable for series requiring a degree of differentiation higher than 0 but lower than 1.

To be more precise, an I(d) or fractionally integrated process is defined as:

$$(1 - L)^d \, x(t) \;=\; u(t), \qquad (1)$$

where L is the backshift (lag) operator (Lx(t) = x(t-1)), d can be any real number (including fractional ones), and u(t) is an I(0) process, which in its simplest form can be a white noise one characterised by zero mean, constant variance and uncorrelated terms.

An appealing feature of such a model is its generality, since it encompasses trend stationary models (if d = 0) as in De Jong et al. (1992a, b), nonstationary unit roots as in

Nelson and Plosser (1982) (if d = 1), but also additional cases corresponding to fractional values, namely:

i) anti-persistence, if $d < 0$;

ii) long-memory covariance stationarity, if $0 < d < 0.5$;

iii) non-stationarity and mean reversion, if $0.5 \leq d < 1$;

iv) long memory after taking first differences, i.e., I(d) with $d > 1$.

In the present context the most relevant case might be (iii), when the series is non-stationary but the effects of shocks are transitory and disappear in the long run.

The polynomial in L in equation (1) can be expanded as in the following expression:

$$(1-L)^d = \sum_{j=1}^{\infty} \frac{\Gamma(\mathrm{d}-1)\,(-L)^j}{\Gamma(\mathrm{d}-\mathrm{j}+1)\,\Gamma(\mathrm{j}+1)}, \tag{2}$$

where Γ is the gamma function, which is defined as:

$$\Gamma(\mathrm{z}) = \int_0^{\infty} t^{z-1} e^{-t}\, d(t). \tag{3}$$

Positive values of d imply 'long memory', namely strong dependence between observations far apart in time. The higher the value of d is, the higher will be their degree of dependence, which implies that shocks will have highly persistent effects and the spectral density function will be unbounded at the origin.

The testing procedure used in the present study was developed by Robinson (1994), and it allows to test for any real value of d using I(d) models and iteration for different values for d_0 (in our case, through 0.01 increments). Specifically, it tests the null hypothesis: H_0: $d = d_0$, for any real value d_0 in equations (1) and (2), and uses a very simple test statistic that follows a standard N(0, 1) distribution; therefore, it allows to construct confidence intervals for all values of d_0 for which the null hypothesis cannot be rejected.

5. Empirical Results

Let x(t) in Equation (1) be the errors in a regression model that includes a constant and a linear time trend, namely:

$$y(t) \;=\; \alpha \;+\; \beta\, t \;\;+\;\; x(t), \qquad (1-L)^d\, x(t) \;=\; u(t), \qquad t \;=1, 2, \ldots \qquad (4)$$

where y(t) denotes the observed series and u(t) is a white noise process.

Table 2 reports the estimates of d for the three cases of a regression 1) without deterministic terms, 2) with a constant only, and 3) with a constant and a linear time trend. We follow a "*general to specific*" approach, starting with 3) and then moving to 2) if the time trend coefficient is found to be statistically insignificant, and to 1) if neither deterministic term is significant. The values reported in bold are those corresponding to the selected model for each series.

INSERT TABLE 2 ABOUT HERE

It can be seen that for 75 out of the 88 series examined the time trend coefficient is statistically significant; in 10 cases (ALBUQ, BAKER, BIRMG, FRESN, HILO, OMAHA, SALTL, SEASTL, TUCSN and WICHT) only the intercept (constant) is significant, while in 3 cases (BRADE, MCALL and PHOEN) neither deterministic trend is significant.

Table 3 displays the estimated coefficients for the selected models. It can be seen that, of the series with significant trends, all except one (SJUAN) exhibit a negative coefficient, which implies that the AQI (and hence pollution) in those areas has been decreasing from 1980 and 2023. The highest coefficients are those corresponding to LANGL (-5.2673) followed by SDIEG (-4.8181), OXND (-4.4790), NYORK (-3.6160) and WASHT (-2.9592).

It should also be noted that the differencing parameter, d, has values higher than 0 (supporting the hypothesis of long memory) in 39 cases. The highest degrees of persistence are found in the cases of FRESN (d = 0.78), BAKER and BRADE (0.76) and SDIEG (0.75). For the remaining 53 series the I(0) hypothesis of short memory cannot be rejected.

INSERT TABLE 3 ABOUT HERE

6. Conclusions

This study provides comprehensive evidence on trends and persistence in air quality in 88 US metropolitan areas for the period 1980-2023, thereby contributing to our understanding of the dynamics of environmental pollution and to policy design. The adopted empirical framework is based on the concept of fractional integration and is ideally suited to detecting long memory, which is found in 65% of the time series examined. This implies that in most cases shocks to pollution levels have long-lasting effects and thus require long-term, sustainable policy actions, and is consistent with the evidence from previous studies that have identified similar persistence patterns in European and Asian countries (Gil Alana et al. 2020; Bhardwaj et al. 2020; Caporale et al. 2021, among others).

More specifically, a statistically significant time trend is found in 75 out of the 87 series analysed. In most cases, the estimated trend is negative, which indicates a general improvement in air quality during the period under investigation, possibly as a result of the implementation of environmental policies such as the Clean Air Act. The most significant improvements appear to have occurred in cities such as Los Angeles, San Diego and Oxnard-Thousand Oaks-Ventura on the Western coast and in New York and Washington on the Eastern coast, where pollution levels decreased sharply

The differencing parameter d is estimated to be greater than 0 in 38 series, which indicates mean reversion in those cases. This implies that, although the effects of shocks to pollution levels are persistent, they eventually die out. The highest values of d are found for Fresno, Bakersfield, Bradenton and San Diego, which appear to be characterised by higher persistence in pollution levels. These differences between metropolitan areas highlight the need for targeted interventions taking into account regional characteristics.

In a number of cases a significant reduction is observed in the number of days with AQI values above 100, especially in cities such as Akron, where this dropped from 55 in 1980 to 9 in 2023, and Albany, where it decreased from 32 to 7 over the same period. However, in other areas such as Fresno and Bakersfield, high levels of pollution have persisted, which confirms the need for policies tailored to the economic, geographic and social characteristics of each region. It is also noteworthy that for 13 of the series analysed the time trend coefficient is statistically insignificant and stationarity is found. Furthermore, the d values for these series support the short memory hypothesis, which points to a lower degree of persistence relative to cities with higher values of d.

On the whole, our findings confirm that regional disparities in pollution levels are significant and that factors such as industrialisation history and extreme weather events strongly influence their degree of persistence. The implication is that, although federal legislation such as the Clean Air Act might be effective to some extent, there is also a need for customised strategies taking into account local socioeconomic characteristics (such as community participation) with the aim of improving air quality. Such an approach can result in more effective and equitable policies addressing the challenges arising from environmental pollution.

Future work could also investigate two additional relevant issues, namely the possible presence of structural breaks and nonlinearities in pollution indices. For the former, the Bai and Perron (2003) tests could be carried out or those specifically designed for the case of fractional integration by Gil-Alana (2008) and Hassler and Meller (2014).

The latter could instead be captured using methods based on Chebyshev's polynomials (Cuestas and Gil-Alana, 2016), Fourier transform functions (Gil-Alana and Yaya, 2021; Caporale et al., 2022) or neural networks (Yaya et al., 2021).

References

Apergis, N.; J.E. Payne, J.E.; M. Topcu, M. (2017). Some empirics on the convergence of carbon dioxide emissions intensity across US states Energy Sources, Part B Econ. Plan. Policy, 1-7. https://doi.org/10.1080/15567249.2017.1310956

Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models, Journal of Applied Econometrics, 18(1), 1-22.

Barrett, S., Speth, R. L., Eastham, S. D., Dedoussi, I. C., Ashok, A., Malina, R., & Keith, D. W. (2015). Impact of the Volkswagen emissions control defeat device on US public health. Environmental Research Letters, 10(11).

Bermejo, L.; Del-Río, M. (2022). Time trends and persistence in PM2.5 in 20 megacities: evidence for the time period 2018–2020,Environmental Science and Pollution Research 30(5):1-18 http://dx.doi.org/10.1007/s11356-022-22512-z

Bevan, GH, Freedman, DA, Lee EK, Rajagopalan, S., Al-Kindi, SG (2021). Association between ambient air pollution and county-level cardiovascular mortality in the United States by social deprivation index. American Heart Journal 235, 125-131, https://doi.org/10.1016/j.ahj.2021.02.005

Bhardwaj, S., Gadre, V. M., and Chandrasekhar, E. (2020). Statistical analysis of DWT coefficients of fGn processes using ARFIMA(p,d,q) models. Physica A: Statistical Mechanics and Its Applications, 124404. https://doi.org/10.1016/j.physa.2020.12440

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

Caporale, G.M., Gil-Alana, L.A.; Carmona-González, N. (2021) Particulate matter 10 (PM10): persistence and trends in eight European capitals. Air Qual Atmos Health 14, 1097–1102. https://doi.org/10.1007/s11869-021-01002-0

Caporale, G.M., Carmona-González, N.; Gil-Alana, L.A (2024). Atmospheric pollution in Chinese cities: Trends and persistence, Heliyon 10, Issue 19, e38211 https://doi.org/10.1016/j.heliyon.2024.e38211

Caporale, G.M., Gil-Alana, L. and O.S. Yaya (2022). Modelling persistence and non-linearities in the US Treasury 10-year bond yields", Economics Bulletin, 42, 3.

Cropper, M. L.; Guttikunda, S.; Jawahar, P.; Lazri, Z.; Malik, K.; Song, X. P.; Yao, X. (2019). Applying benefit-cost analysis to air pollution control in the Indian power sector. Journal of Benefit-Cost Analysis, 10(S1), 185-205. https://doi.org/10.1017/bca.2018.27

Cuestas J.C. and L.A. Gil-Alana (2016). A Non-Linear Approach with Long Range Dependence Based on Chebyshev Polynomials, Studies in Nonlinear Dynamics and Econometrics, 23, 445–468.

De Jong, D., J. Nankervis, N.E. Savin and C.H. Whiteman (1992a), Integration versus trend stationarity in time series, Econometrica 60, 423-433.

De Jong, D.N., J.C. Nankervis and N.F. Savin (1992b). The power problems of unit root test in time series with auto- regressive errors. Journal of Econometrics 53(1-3), 323-343.

EPA (U.S. Environmental Protection Agency, 2024a). Sources of Greenhouse Gas Emissions. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

EPA (U.S. Environmental Protection Agency, 2024b). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2022. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2022

EPA (U.S. Environmental Protection Agency, 2024c). Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI). https://document.airnow.gov/technical-assistance-document-for-the-reporting-of-daily-air-quailty.pdf

Gil-Alana, L.A. (2008). Fractional integration and structural breaks at unknown periods of time. Journal of Time Series Analysis, 29, 163-185.

Gil-Alana LA, Solarin SA (2018) Have U.S. environmental policies been effective in the reduction of U.S. emissions? A new approach using fractional integration, Atmospheric Pollution Research, Volume 9, Issue 1, 53-60,https://doi.org/10.1016/j.apr.2017.06.008.

Gil-Alana, L.A.; Trani, T. (2019). Time Trends and Persistence in the Global CO2 Emissions Across Europe, Environmental & Resource Economics , Spri
nger; European Association of Environmental and Resource Economists, vol. 73(1), 213-228. https://doi.org/10.1007/s10640-018-0257-5

Gil-Alana, L.A. and O. Yaya (2021). Testing fractional unit roots with non-linear smooth break approximations using Fourier functions. Journal of Applied Statistics 48 (13-15), 2542-2559.

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

Gil-Alana LA, Yaya O, Awolaja O, Cristofaro L (2020b) Long Memory and Time Trends in Particulate Matter Pollution (PM2.5 and PM10) in the US State. J Appl Meteorol Climatol 59(8):1351–1367 https://dx.doi.org/10.1175/JAMC-D-20-0040.1

Gil-Alana LA, Lenti J (2021) Time trends and persistence in European temperatura anomalies. Int J Climatol 419:4619–4636 https://dx.doi.org/10.1002/joc.7090

Gil-Alana, LA, Gupta, R., Sauci, L., Carmona-González, N. (2022). Temperature and precipitation in the US states: long memory, persistence, and time trends, Theoretical and Applied Climatology 150, 1731–1744 https://doi.org/10.1007/s00704-022-04232-z

Granger, C.W.J. (1966) The typical spectral shape of an economic variable. Econometrica 34(1), 150-161.

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

Granger, C.W.J., y R. Joyeux. (1980). An Introduction to Long Memory Time Series and Fractional Differencing. Journal of Time Series Analysis 1(1): 15-29. https://doi.org/10.1111/j.1467-9892.1980.tb00297.x

Hannah Ritchie (2019). Who has contributed most to global CO2 emissions? Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/contributed-most-global-co2'

Hassler, U., and B. Meller (2014). Detecting multiple breaks in long memory. The case of US inflation, Empirical Economics 46, 2, 653-680.

Hsiang, S., Kopp, RE, Jina, A., Rising, J., Delgado M., Mohan, S., Rasmussen, DJ, Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K. y T. Houser. (2017). Estimating economic damage from climate change in the United States, Science 356, 1362-1369. https://www.science.org/doi/10.1126/science.aal4369

Huang, H-H., Chan, N.H., Chen, K., Ing, C-K. (2022). Consistent order selection for ARFIMA processes. The Annals of Statistics, 50(3) 1297 – 1319 https://doi.org/10.1142/S1793042105000030

Ismail, L.A.; Awang, N.; Kane, I.L. (2023). Investigating the Degree of Persistence, Trend and the Best Time Series Forecasting Models for Particulate Matter (PM10) Pollutant Across Malaysia, MJFAS, 19, 5 https://doi.org/10.11113/mjfas.v19n5.2965

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

Maji, KJ; Li,Z. Hu, Y.; Vaidyanathan, A.; Stowell, JD; Milando, C.; Wellenius,G.; Kinney, P.L.; Russell, , A.G.; Odman, M.T. (2024). Prescribed burn related increases of population exposure to PM2.5 and O3 pollution in the southeastern US over 2013–2020, Environment International 193, 109101, https://doi.org/10.1016/j.envint.2024.109101

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

Nelson, C.R. and C.I. Plosser (1982), Trends and random walks in macroeconmic time series. Journal of Monetary Economics 34(1), 167-180.

Ni, Yu a,b ; Sullivan, Alexis c ; Szpiro, Adam AD ; Peng, James d ; Loftus, Christine TA ; Hazlehurst, Marnie F. a ; Sherris, Allison a ; Wallace, Erin RA ; Murphy, Laura E.e ; Nguyen, Ruby HN f ; Swan, Shanna H. g ; Sathyanarayana, Sheela a,h,i ; Barrett, Emily Sj ; Mason, W. Alex k ; Bush, Nicole R. c, l ; Karr, Catherine J. a,h,m ; LeWinn, Kaja Z.c. (2024). Ambient Air Pollution Exposures and Child Executive Function: A US Multicohort Study. Epidemiology 35(5), 676-688 https://doi.org/10.1097/ede.0000000000001754

NOAA (National Centers for Environmental Information) (2025). Billion-Dollar Weather and Climate Disasters. https://www.ncei.noaa.gov/access/billions/time-series

Payne, J.E.; Miller, S. Lee, J.; Cho, M.H. (2014). Convergence of per capita sulphur dioxide emissions across US states, Appl. Econ., 46 (11) 1202-1211 https://doi.org/10.1080/00036846.2013.868588

Pandey, A.; Brauer, M.; Cropper, M. L.; Balakrishnan, K.; Mathur, P.; Dey, S., Dandona, L. (2021). Health and economic impact of air pollution in the states of India: the Global Burden of Disease Study 2019. The Lancet Planetary Health, 5(1), e25-e38. https://doi.org/10.1016/s2542-5196(20)30298-9

Plaia, A., and Ruggieri, M. (2011) Air quality indices: a review, Rev. Environ. Sci. Biotechnol. 10:165–179. DOI 10.1007/s11157-010-9227-2

Pokharel, A., Hennessy, D., Wu, F. (2023). Health burden associated with tillage-related PM2.5 pollution in the United States, and mitigation strategies, Science of The Total Environment 903, 166161, https://doi.org/10.1016/j.scitotenv.2023.166161

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

Rubio. R., Grineski, S., Collins, T. (2022). Carcinogenic air pollution along the United States' southern border: Neighborhood inequities in risk, Environmental Research 212, Part B, 113251, https://doi.org/10.1016/j.envres.2022.113251.

Sakiru S, Gil-Alana LA, Gonzalez-Blanch MJ (2021) Persistence of sulphur dioxide emissions in OECD countries. Int J Environ Res 15:701–708 https://doi.org/10.1007/s41742-021-00347-9

Smith, B. (2023). 2022 U.S. billion-dollar weather and climate disasters in historical context. 2022 U.S. billion-dollar weather and climate disasters in historical context | NOAA Climate.gov 2022 U.S. billion-dollar weather and climate disasters in historical context | NOAA Climate.gov

U.S. Environmental Protection Agency, Office of Air and Radiation, Air Trends, Air Quality Index: Daily AQI, available at https://aqs.epa.gov/aqsweb/airdata/download_files.html as of Dec. 11, 2024.

Yaya OS, Awolaja OG, Okedina IM, Vo XV (2020) Air quality level in California US state: persistence and seasonality. Theor Appl Climatol 142:1471–1479 https://doi.org/10.1007/s00704-020-03376-0

Yaya, O.S., Ogbonna, A.E., Furuoka, F., and Gil-Alana, L.A. (2021). A new unit root test for unemployment hysteresis based on the autoregressive neural network. Oxford Bulletin of Economics and Statistics, 83(4), 960-981.

Yuan N, Huang Y, Duan J, Zhu C, Xoplaki E, Luterbacher J (2019) On climate prediction. How much can we expect from climate memory? Climate Dynamics 52(1-2):855–864 https://doi.org/10.1007/s00382-018-4168-5

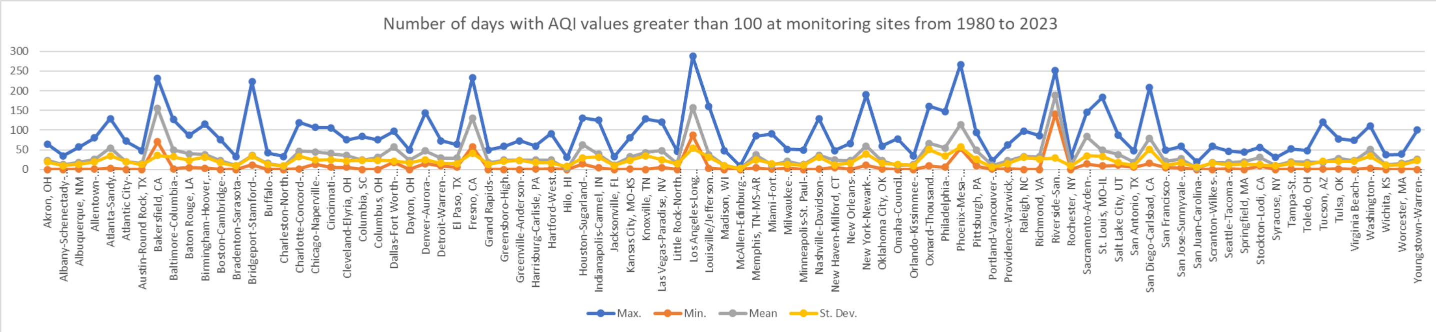

Figure 1: Descriptive statistics for the number of days with AQI values greater than 100 from 1980 to 2023.

Table 1: Descriptive Statistics

District	Acronym	Max.	Min.	Mean	St. Dev.
Akron, OH	AKRON	65	0	22.97	19.18
Albany-Schenectady-Troy, NY	ALBAN	35	0	12.19	9.98
Albuquerque, NM	ALBUQ	57	1	18.31	13.04
Allentown-Bethlehem-Easton, PA	ALLEN	80	1	25.50	19.04
Atlanta-Sandy Springs-Roswell, GA	ATLAA	129	3	54.94	35.08
Atlantic City-Hammonton, NJ	ATLIC	72	0	19.50	20.09
Austin-Round Rock, TX	AUSTI	48	0	15.25	12.20
Bakersfield, CA	BAKER	231	70	154.86	35.52
Baltimore-Columbia-Towson, MD	BALTM	127	2	49.83	32.04
Baton Rouge, LA	BATON	87	5	39.53	23.56
Birmingham-Hoover, AL	BIRMG	115	3	38.44	31.36
Boston-Cambridge-Newton, MA-NH	BOSTN	75	0	22.08	17.15
Bradenton-Sarasota-Venice, FL	BRADE	32	0	10.08	9.49
Bridgeport-Stamford-Norwalk, CT	BRIDG	223	12	35.83	33.91
Buffalo-Cheektowaga-Niagara Falls, NY	BUFFL	42	0	16.03	13.30
Charleston-North Charleston, SC	CHLTN	33	0	8.67	8.96
Charlotte-Concord-Gastonia, NC-SC	CHRLT	119	2	46.67	33.29
Chicago-Naperville-Joliet, IL-IN-WI	CHICG	107	13	45.00	24.20
Cincinnati-Middletown, OH-KY-IN	CINCN	106	6	40.19	25.25
Cleveland-Elyria, OH	CLEVL	75	6	35.31	21.30
Columbia, SC	CLMBA	84	0	23.78	23.21
Columbus, OH	COLUM	75	0	30.75	23.09
Dallas-Fort Worth-Arlington, TX	DALLA	97	18	56.94	21.21
Dayton, OH	DAYTN	50	0	23.08	16.24
Denver-Aurora-Lakewood, CO	DENVR	144	15	47.08	24.86
Detroit-Warren-Dearborn, MI	DETRT	73	9	29.03	15.52
El Paso, TX	ELPAS	64	6	28.86	14.93
Fresno, CA	FRESN	233	58	130.61	41.01
Grand Rapids-Wyoming, MI	GRAND	50	0	17.31	13.41
Greensboro-High Point, NC	GRNBO	59	0	23.81	20.89
Greenville-Anderson-Mauldin, SC	GRNVL	73	0	23.56	23.32

(cont.)

Table 1: Descriptive Statistics (cont.)

	Acronym	Max.	Min.	Mean	St. Dev.
Harrisburg-Carlisle, PA	HARRB	60	1	24.19	17.47
Hartford-West Hartford-East Hartford, CT	HARTW	91	2	24.42	16.45
Hilo, HI	HILO	31	0	2.58	7.07
Houston-Sugarland-Baytown, TX	HOUST	131	14	63.08	29.64
Indianapolis-Carmel, IN	INDIA	125	4	38.75	31.32
Jacksonville, FL	JAKVL	32	0	11.69	9.66
Kansas City, MO-KS	KANSC	81	1	32.19	22.95
Knoxville, TN	KNOXV	128	0	43.19	34.61
Las Vegas-Paradise, NV	LVEGS	121	5	48.28	24.67
Little Rock-North Little Rock-Conway, AR	LTTRK	46	0	16.00	14.33
Los Angeles-Long Beach-Anaheim, CA	LANGL	287	87	157.14	54.14
Louisville/Jefferson County, KY-IN	LOUVL	161	3	38.47	31.77
Madison, WI	MADIS	48	0	9.61	9.73
McAllen-Edinburg-Mission, TX	MCALL	9	0	2.08	2.73
Memphis, TN-MS-AR	MEMPS	85	4	37.14	25.19
Miami-Fort Lauderdale-West Palm Beach, FL	MIAMI	90	1	11.83	15.22
Milwaukee-Waukesha-West Allis, WI	MILWK	51	3	20.75	13.37
Minneapolis-St. Paul-Bloomington, MN-WI	MINNP	50	0	12.64	11.04
Nashville-Davidson-Murfreesboro-Franklin, TN	NASHV	129	1	36.14	31.11
New Haven-Milford, CT	NHAVN	48	5	23.67	11.64
New Orleans-Metairie, LA	NORLS	66	0	22.22	16.53
New York-Newark-Jersey City, NY-NJ-PA	NYORK	190	11	60.00	39.55
Oklahoma City, OK	OKLAH	60	2	22.53	15.50
Omaha-Council Bluffs, NE-IA	OMAHA	78	0	10.36	13.54
Orlando-Kissimmee-Sanford, FL	ORLND	35	0	12.17	9.78
Oxnard-Thousand Oaks-Ventura, CA	OXNRD	161	9	66.31	50.18
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	PHILD	147	6	54.83	33.71
Phoenix-Mesa-Scottsdale, AZ	PHOEN	267	54	114.22	57.22
Pittsburgh, PA	PITTS	94	9	48.75	25.93
Portland-Vancouver-Hillsboro, OR-WA	PORTL	22	1	10.75	6.04
Providence-Warwick, RI-MA	PROVD	63	2	22.25	14.86

(cont.)

Table 1: Descriptive Statistics (cont.)

	Acronym	Max.	Min.	Mean	St. Dev.
Raleigh, NC	RALGH	98	0	32.97	30.73
Richmond, VA	RICHM	86	0	32.19	26.15
Riverside-San Bernardino-Ontario, CA	RIVSD	251	141	188.06	28.83
Rochester, NY	ROCHT	32	0	10.50	9.48
Sacramento-Arden-Arcade-Roseville, CA	SACRM	145	14	83.39	34.44
St. Louis, MO-IL	STLOU	183	9	48.94	33.23
Salt Lake City, UT	SALTL	87	11	37.94	17.51
San Antonio, TX	SANTO	47	6	18.19	10.18
San Diego-Carlsbad, CA	SDIEG	209	16	79.39	51.05
San Francisco-Oakland-Hayward, CA	SFRAN	49	5	20.31	10.32
San Jose-Sunnyvale-Santa Clara, CA	SJOSE	59	4	27.53	17.47
San Juan-Carolina-Caguas, PR	SJUAN	19	0	3.67	5.97
Scranton-Wilkes-Barre-Hazleton, PA	SCRNT	59	0	17.47	16.28
Seattle-Tacoma-Bellevue, WA	SEATL	46	2	17.28	11.23
Springfield, MA	SPRING	44	0	20.06	14.02
Stockton-Lodi, CA	STOCK	56	9	30.94	12.54
Syracuse, NY	SYRAC	31	0	10.00	8.98
Tampa-St. Petersburg-Clearwater, FL	TAMPA	52	1	19.67	15.36
Toledo, OH	TOLED	48	1	18.47	12.78
Tucson, AZ	TUCSN	120	1	18.39	20.42
Tulsa, OK	TULSA	78	2	28.25	20.42
Virginia Beach-Norfolk-Newport News, VA-NC	VIRGN	74	0	22.39	20.62
Washington-Arlington-Alexandria, DC-VA-MD-WV	WASHT	111	3	50.19	33.69
Wichita, KS	WICHT	37	0	11.86	10.67
Worcester, MA	WORCT	39	0	15.97	12.13
Youngstown-Warren-Boardman, OH	YOUNG	100	0	26.81	22.11

Note: this table reports the maximum and minimum value, the mean and the standard deviation for each AQI series.

Table 2: Estimates of d

Series	No deterministic terms	An intercept	An intercept and a linear time trend
AKRON	0.54 (0.39, 0.75)	0.41 (0.31, 0.54)	**0.11 (-0.08, 0.36)**
ALBAN	0.47 (0.31, 0.72)	0.35 (0.24, 0.51)	**0.10 (-0.10, 0.37)**
ALBUQ	0.22 (-0.02, 0.49)	**0.18 (-0.02, 0.48)**	0.17 (-0.07, 0.67)
ALLEN	0.54 (0.34, 0.83)	0.41 (0.29, 0.58)	**0.19 (-0.09, 0.71)**
ATLAA	0.65 (0.49, 0.89)	0.51 (0.39, 0.71)	**0.32 (0.10, 0.65)**
ATLIC	0.54 (0.37, 0.79)	0.40 (0.29, 0.52)	**0.11 (-0.09, 0.41)**
AUSTI	0.40 (0.24, 0.64)	0.30 (0.17, 0.48)	**0.01 (-0.19, 0.31)**
BAKER	0.81 (0.61, 1.09)	**0.76 (0.55, 1.12)**	0.75 (0.52, 1.12)
BALTM	0.63 (0.44, 0.91)	0.44 (0.34, 0.56)	**-0.08 (-0.35, 0.31)**
BATON	0.70 (0.51, 1.00)	0.50 (0.37, 0.70)	**0.19 (-0.04, 0.58)**
BIRMG	0.74 (0.54, 1.09)	**0.68 (0.48, 1.05)**	0.65 (0.41, 1.05)
BOSTN	0.50 (0.31, 0.79)	0.38 (0.24, 0.58)	**0.19 (-0.11, 0.88)**
BRADE	**0.76 (0.59, 1.07)**	0.73 (0.54, 1.06)	0.72 (0.49, 1.06)
BRIDG	0.07 (-0.21, 0.43)	0.04 (-0.15, 0.30)	**0.12 (-0.18, 0.42)**
BUFFL	0.46 (0.27, 0.74)	0.35 (0.21, 0.53)	**0.16 (-0.04, 0.46)**
CHLTN	0.44 (0.24, 0.74)	0.35 (0.19, 0.62)	**0.12 (-0.25, 0.78)**
CHRLT	0.65 (0.49, 0.89)	0.49 (0.37, 0.69)	**0.35 (0.12, 0.74)**
CHICG	0.54 (0.37, 0.79)	0.34 (0.19, 0.53)	**0.16 (-0.10, 0.50)**
CINCN	0.40 (0.24, 0.64)	0.35 (0.22, 0.53)	**0.06 (-0.18, 0.45)**
CLEVL	0.81 (0.61, 1.09)	0.47 (0.36, 0.61)	**0.28 (0.11, 0.51)**
CLMBA	0.63 (0.44, 0.91)	0.35 (0.23, 0.52)	**0.16 (-0.07, 0.50)**
COLUM	0.70 (0.51, 1.00)	0.41 (0.30, 0.55)	**0.11 (-0.07, 0.38)**
DALLA	0.74 (0.54, 1.09)	0.52 (0.35, 0.87)	**0.41 (0.08, 0.87)**
DAYTN	0.50 (0.31, 0.79)	0.38 (0.27, 0.73)	**0.17 (-0.03, 0.41)**
DENVR	-0.09 (-0.21, 0.60)	-0.06 (-0.35, 1.18)	**0.12 (-0.15, 1.17)**
DETRT	0.42 (0.23 0.69)	0.29 (0.15, 0.47)	**0.11 (-0.12, 0.44)**
EL PAS	0.60 (0.39, 0.90)	0.41 (0.25, 0.64)	**0.30 (0.09, 0.60)**
FRESN	0.76 (0.51, 1.16)	**0.78 (0.49, 1.21)**	0.79 (0.50, 1.21)
GRAND	0.44 (0.26, 0.70)	0.31 (0.18, 0.48)	**-0.08 (-0.33, 0.26)**
GRNBO	0.70 (0.52, 1.03)	0.58 (0.43, 0.86)	**0.44 (0.20, 0.84)**
GRNVL	0.52 (0.37, 0.74)	0.46 (0.33, 0.67)	**0.39 (0.19, 0.69)**

Table 2: Estimates of d (cont.)

Series	No deterministic terms	An intercept	An intercept and a linear time trend
HARRB	0.58 (0.43, 0.81)	0.44 (0.33, 0.58)	**0.13 (-0.05, 0.39)**
HARTW	0.40 (0.18, 0.70)	0.26 (0.12, 0.44)	**0.08 (-0.24, 1.07)**
HILO	0.43 (0.14, 0.89)	**0.44 (0.15, 0.89)**	0.43 (0.11, 0.89)
HOUST	0.82 (0.58, 1.22)	0.60 (0.43. 1.03)	**0.55 (0.17, 1.03)**
INDIA	0.64 (0.44, 0.97)	0.58 (0.39, 1.07)	**0.58 (0.26, 1.07)**
JAKVL	0.56 (0.40, 0.79)	0.46 (0.33, 0.66)	**0.29 (0.06, 0.63)**
KANSC	0.54 (0.32, 0.88)	0.43 (0.26, 0.77)	**0.28 (-0.01, 0.79)**
KNOXV	0.75 (0.57, 1.03)	0.63 (0.49, 0.89)	**0.55 (0.32, 0.86)**
LVEGS	0.47 (0.21, 0.83)	0.31 (0.12, 0.66)	**0.29 (-0.08, 0.80)**
LTTRK	0.43 (0.25, 0.70)	0.34 (0.18, 0.56)	**0.16 (-0.07, 0.53)**
LANGL	0.77 (0.56, 1.10)	0.52 (0.40, 0.75)	**0.57 (0.33, 0.89)**
LOUVL	0.33 (0.11 0.63)	0.24 (0.08, 0.48)	**0.03 (-0.32, 0.98)**
MADIS	0.31 (0.01, 0.74)	0.20 (0.01, 0.50)	**0.00 (0.37, 0.57)**
MCALL	**0.51 (0.33, 0.72)**	0.51 (0.34, 0.72)	0.51 (0.35, 0.72)
MEMPS	0.60 (0.44, 0.82)	0.48 (-0.36, 0.65)	**0.28 (0.08, 0.61)**
MIAMI	0.10 (-0.21, 0.45)	0.07 (-0.11, 0.34)	**0.01 (-0.31, 0.45)**
MILWK	0.47 (0.27, 0.77)	0.28 (0.15, 0.46)	**-0.12 (-0.38, 0.25)**
MINNP	0.52 (0.21, 1.02)	0.36 (0.14, 0.76)	**0.30 (-0.11, 0.78)**
NASHV	0.63 (0.48, 0.87)	0.53 (0.39, 0.76)	**0.37 (0.12, 0.72)**
NHAVN	0.52 (0.33, 0.80)	0.34 (0.21, 0.51)	**0.03 -(0.22, 0.40)**
NORLS	0.68 (0.46, 1.11)	0.49 (0.33, 0.78)	**0.20 (-0.06, 0.72)**
NYORK	0.66 (0.40, 1.12)	0.43 (0.28, 0.63)	**0.37 (0.00, 0.74)**
OKLAH	0.47 (0.25, 0.82)	0.35 (0.18, 0.63)	**0.17 (-0.06, 0.58)**
OMAHA	0.30 (-0.09, 0.80)	**0.28 (-0.08, 0.63)**	0.74 (0.00, 1.22)
ORLND	0.66 (0.50, 0.90)	0.57 (0.42, 0.81)	**0.47 (0.23, 0.79)**
OXND	0.82 (0.63, 1.13)	0.60 (0.50, 0.74)	**0.40 (0.20, 0.70)**
PHILD	0.67 (0.46, 1.07)	0.46 (0.35, 0.60)	**0.02 (-0.38, 0.64)**
PHOEN	**0.29 (0.01, 1.00)**	0.33 (0.02, 1.03)	0.20 (-0.14, 1.03)
PITTS	0.62 (0.45, 0.87)	0.54 (0.40, 0.77)	**0.50 (0.33, 0.77)**
PORTL	-0.11 (-0.21, 0.39)	-0.07 (-0.32, 0.21)	**-0.06 (-0.29, 0.24)**
PROVD	0.67 (0.44, 1.06)	0.47 (0.33, 0.79	**0.39 (0.00, 0.85)**

Table 2: Estimates of d (cont.)

Series	No deterministic terms	An intercept	An intercept and a linear time trend
RALGH	0.64 (0.48, 0.89)	0.57 (0.43, 0.96)	**0.54 (0.28, 0.98)**
RICHM	0.66 (0.50, 0.92)	0.48 (0.39, 0.64)	**-0.02 (-0.25, 0.34)**
RIVSD	0.79 (0.58, 1.09)	0.43 (0.30, 0.60)	**0.25 (0.00, 0.60)**
ROCHT	0.52 (0.31, 0.84)	0.34 (0.21, 0.52)	**-0.21 (-0.56, 0.24)**
SACRM	0.63 (0.44, 0.88)	0.45 (0.31, 0.67)	**0.31 (0.10, 0.62)**
STLOU	0.34 (0.12, 0.65)	0.24 (0.08, 0.45)	**0.01 (-0.34, 1.16)**
SALTL	0.06 (-0.08, 0.39)	**0.07 (-0.14, 0.38)**	0.13 (-0.11, 0.60)
SANTO	0.35 (0.16, 0.61)	0.26 (0.11, 0.48)	**0.14 (0.06, 0.44)**
SDIEG	0.86 (0.63, 1.23)	0.67 (0.51, 1.02)	**0.75 (0.56, 1.01)**
SFRAN	0.46 (0.21, 0.81)	0.33 (0.15, 0.70)	**0.35 (0.05, 0.79)**
SJOSE	0.63 (0.45, 0.89)	0.44 (0.33, 0.59)	**0.16 (-0.08, 0.47)**
SJUAN	0.45 (0.26, 0.74)	0.46 (0.28, 0.74)	**0.39 (0.17, 0.73)**
SCRNT	0.50 (0.35, 0.72)	0.38 (0.27, 0.50)	**-0.04 (-0.27, 0.26)**
SEATL	0.24 (-0.02, 0.53)	**0.20 (-0.01, 0.49)**	0.27 (0.02, 0.63)
SPRING	0.81 (0.61, 1.15)	0.54 (0.43, 0.72)	**-0.07 (-0.27, 0.32)**
STOCK	0.27 (-0.23, 0.64)	0.06 (-0.15, 0.32)	**-0.08 (-0.31, 0.26)**
SYRAC	0.49 (0.32, 0.74)	0.35 (0.23, 0.51)	**-0.04 (0.27, 0.28)**
TAMPA	0.73 (0.51, 1.12)	0.57 (0.41, 0.90)	**0.45 (0.17, 0.89)**
TOLED	0.46 (0.29, 0.90)	0.34 (0.22, 0.50)	**0.14 (-0.05, 0.41)**
TUCSN	0.26 (0.03, 0.57)	**0.19 (0.02, 0.46)**	0.94 (0.03, 1.46)
TULSA	0.54 (0.32, 0.89)	0.38 (0.22, 0.69)	**0.11 (0.32, 0.77)**
VIRGN	0.53 (0.39, 0.75)	0.41 (0.33, 0.53)	**-0.04 (-0.31, 0.32)**
WASHT	0.73 (0.54, 1.03)	0.50 (0.40, 0.62)	**-0.12 (-0.38, 0.29)**
WICHT	0.63 (-0.37, 1.06)	**0.59 (0.32, 1.04)**	0.58 (0.30, 1.04)
WORCT	0.52 (0.36, 0.74)	0.42 (0.30, 0.59)	**0.20 (0.00, 0.50)**
YOUNG	0.39 (0.23, 0.60)	0.28 (0.17, 0.41)	**-0.22 (-0.46, 0.11)**

Note: the coefficients from the selected model are in bold. In brackets the 95% confidence bands

Table 3: Coefficient Estimates

Series	No deterministic terms	An intercept	An intercept and a linear time trend
AKRON	0.11 (-0.08, 0.36)	49.8737 (10.54)	-1.4500 (-6.70)
ALBAN	0.10 (-0.10, 0.37)	25.6817 (9.00)	-0.7424 (-5.36)
ALBUQ	0.18 (-0.02, 0.48)	19.0291 (5.24)	-----
ALLEN	0.19 (-0.09, 0.71)	55.0732 (11.14)	-1.5672 (-7.01)
ATLAA	0.32 (0.10, 0.65)^{LM}	93.5685 (6.99)	-2.2599 (-3.70)
ATLIC	0.11 (-0.09, 0.41)	50.5064 (11.56)	-1.6467 (-8.23)
AUSTI	0.01 (-0.19, 0.31)	28.0410 (8.37)	-0.6919 (-4.39)
BAKER	0.76 (0.55, 1.12)^{LM}	131.7347 (6.17)	-----
BALTM	-0.08 (-0.35, 0.31)	100.8621 (26.98)	-2.7626 (-15.27)
BATON	0.19 (-0.04, 0.58)	70.9378 (10.42)	-1.7189 (-5.58)
BIRMG	0.68 (0.48, 1.05)^{LM}	52.7377 (3.01)	-----
BOSTN	0.19 (-0.11, 0.88)	47.8229 (9.47)	-1.3513 (-5.92)
BRADE	0.76 (0.59, 1.07)^{LM}	-----	-----
BRIDG	0.12 (-0.18, 0.42)	72.0704 (5.68)	-1.8432 (-3.18)
BUFFL	0.16 (-0.04, 0.46)	32.0667 (7.12)	-0.8616 (-4.22)
CHLTN	0.12 (-0.25, 0.78)	20.0627 (7.36)	-0.6085 (-4.89)
CHRLT	0.35 (0.12, 0.74)^{LM}	96.6228 (8.62)	-2.6666 (-5.16)
CHICG	0.16 (-0.10, 0.50)	74.9967 (9.05)	-1.5771 (-4.19)
CINCN	0.06 (-0.18, 0.45)	74.6703 (12.21)	-1.8593 (-6.56)
CLEVL	0.28 (0.11, 0.51)^{LM}	60.3097 (7.85)	-1.4872 (-4.27)
CLMBA	0.16 (-0.07, 0.50)	54.9217 (7.68)	-1.6603 (-5.11)
COLUM	0.11 (-0.07, 0.38)	62.3232 (10.62)	-1.7136 (-6.38)
DALLA	0.41 (0.08, 0.87)^{LM}	85.2416 (8.41)	-1.3857 (-2.88)
DAYTN	0.17 (-0.03, 0.41)	42.4424 (8.03)	-1.0644 (-4.44)
DENVR	0.12 (-0.15, 1.17)	63.2683 (6.15)	-0.8100 (-1.72)
DETRT	0.11 (-0.12, 0.44)	46.4990 (9.15)	-0.9331 (-4.01)
EL PAS	0.30 (0.09, 0.60)^{LM}	40.8169 (5.71)	-0.6851 (-2.10)
FRESN	0.78 (0.49, 1.21)^{LM}	160.6869 (6.62)	------
GRAND	-0.08 (-0.33, 0.26)	33.4215 (12.04)	-0.8719 (-6.48)
GRNBO	0.44 (0.20, 0.84)^{LM}	44.4925 (4.87)	-1.2537 (-2.82)
GRNVL	0.39 (0.19, 0.69)^{LM}	52.8785 (5.08)	-1.5504 (-3.17)

Table 3: Coefficients Estimates (cont.)

Series	No deterministic terms	An intercept	An intercept and a linear time trend
HARRB	0.13 (-0.05, 0.39)	47.4469 (10.21)	-1.2679 (-5.98)
HARTF	0.08 (-0.24, 1.07)	47.9171 (11.62)	-1.2500 (-6.58)
HILO	0.13 (-0.05, 0.39)	-----	-----
HOUST	0.55 (0.17, 1.03)LM	116.3852 (8.61)	-2.3171 (-3.13)
INDIA	0.58 (0.26, 1.07)LM	82.4697 (4.64)	-1.9849 (-1.95)
JAKVL	0.29 (0.06, 0.63)LM	24.0426 (6.85)	-0.6848 (-4.30)
KANSC	0.28 (-0.01, 0.79)	57.6581 (5.75)	-1.3444 (-2.96)
KNOXV	0.55 (0.32, 0.86)LM	71.3225 (4.42)	-1.9169 (-2.17)
LVEGS	0.29 (-0.08, 0.80)	83.8818 (7.77)	-1.7711 (-3.62)
LTTRK	0.16 (-0.07, 0.53)	32.8537 (6.66)	-0.9093 (-4.06)
LANGL	0.57 (0.33, 0.89)LM	272.4335 (15.93)	-5.2673 (-5.47)
LOUVL	0.03 (-0.32, 0.98)	76.0910 (8.97)	-2.0262 (-5.11)
MADIS	0.00 (0.37, 0.57)LM	17.9349 (6.28)	-0.4499 (-3.34)
MCALL	0.51 (0.33, 0.72)LM	-----	-----
MEMPS	0.28 (0.08, 0.61)LM	71.1849 (8.55)	-1.8465 (-4.89)
MIAMI	0.01 (-0.31, 0.45)	26.6894 (6.11)	-0.8006 (-3.90)
MILWK	-0.12 (-0.38, 0.25)	35.9376 (13.66)	-0.8279 (-6.40)
MINNP	0.30 (-0.11, 0.78)	25.7462 (4.40)	-0.5759 (-2.16)
NASHV	0.37 (0.12, 0.72)LM	59.0678 (4.21)	-1.5339 (-2.35)
NHAVN	0.03 -(0.22, 0.40)	39.2725 (14.54)	-0.8426 (-6.68)
NORLS	0.20 (-0.06, 0.72)	41.7708 (7.49)	-1.0836 (-4.30)
NYORK	0.37 (0.00, 0.74)LM	134.9215 (9.76)	-3.6160 (-5.63)
OKLAH	0.17 (-0.06, 0.58)	35.9194 (5.84)	-0.7466 (-2.68)
OMAHA	0.28 (-0.08, 0.63)	55.9665 (5.08)	------
ORLND	0.47 (0.23, 0.79)LM	17.276 (3.46)	-0.4275 (-1.72)
OXND	0.40 (0.20, 0.77)LM	154.754 (14.40)	-4.4790 (-8.83)
PHILD	0.02 (-0.38, 0.64)	109.0912 (22.71)	-2.9282 (-13.01)
PHOEN	0.29 (0.01, 1.00)LM	-----	------
PITTS	0.50 (0.33, 0.77)LM	79.3010 (6.39)	-1.7027 (-2.65)
PORTL	-0.06 (-0.29, 0.24)	14.0159 (8.34)	-0.1771 (-2.19)
PROVD	0.39 (0.00, 0.85)LM	49.4771 (9.32)	-1.3184 (-5.29)

Table 3: Coefficient Estimates (cont.)

Series	No deterministic terms	An intercept	An intercept and a linear time trend
RALGH	0.54 (0.28, 0.98)^{LM}	80.7851 (6.20)	-2.3521 (-3.35)
RICHM	-0.02 (-0.25, 0.34)	72.7732 (18.27)	-2.1929 (-11.60)
RIVSD	0.25 (0.00, 0.60)^{LM}	234.9260 (29.52)	-2.4557 (-6.83)
ROCHT	-0.21 (-0.56, 0.24)	22.8543 (17.29)	-0.6776 (-10.08)
SACRM	0.31 (0.10, 0.62)^{LM}	126.0146 (9.51)	-2.4501 (-4.06)
STLOU	0.01 (-0.34, 1.16)	90.3870 (11.21)	-2.2378 (-5.91)
SALTL	0.07 (-0.14, 0.38)	38.2576 (8.96)	-----
SANTO	0.14 (0.06, 0.44)^{LM}	26.4461 (8.66)	-0.4526 (-2.50)
SDIEG	0.75 (0.56, 1.01)^{LM}	204.1215 (13.13)	-4.8181 (-3.83)
SFRAN	0.35 (0.05, 0.79)^{LM}	34.2575 (6.54)	-0.6787 (-2.50)
SJOSE	0.16 (-0.08, 0.47)	53.9906 (12.99)	-1.4218 (-2.50)
SJUAN	0.39 (0.17, 0.73)^{LM}	-15.2980 (-2.48)	0.3159 (2.13)
SCRNT	-0.04 (-0.27, 0.26)	41.6362 (15.58)	-1.3098 (-10.27)
SEATL	0.20 (-0.01, 0.49)	19.3022 (4.80)	-----
SPRING	-0.07 (-0.27, 0.32)	42.3304 (23.44)	-1.2020 (-13.79)
STOCK	-0.08 (-0.31, 0.26)	42.1167 (14.05)	-0.6023 (-4.15)
SYRAC	-0.04 (0.27, 0.28)^{LM}	21.6794 (11.62)	-0.6323 (-7.10)
TAMPA	0.45 (0.17, 0.89)^{LM}	38.1600 (5.58)	-1.0287 (-2.68)
TOLED	0.14 (-0.05, 0.41)	33.9437 (8.29)	-0.8298 (-4.45)
TUCSN	0.19 (0.02, 0.46)^{LM}	114.5991 (7.82)	-----
TULSA	0.11 (0.32, 0.77)^{LM}	54.3395 (9.01)	-1.3930 (-5.04)
VIRGN	-0.04 (-0.31, 0.32)	54.2184 (17.93)	-1.7240 (-11.94)
WASHT	-0.12 (-0.38, 0.29)	104.7855 (30.88)	-2.9592 (-17.75)
WICHT	0.59 (0.32, 1.04)^{LM}	12.4444 (1.88)	-----
WORCT	0.20 (0.00, 0.50)^{LM}	31.4616 (8.14)	-0.8505 (-4.87)
YOUNG	-0.22 (-0.46, 0.11)	58.1530 (23.08)	-1.7083 (-13.28)

Note: in brackets the 95% confidence bands.