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Particulate Matter 2.5 ($PM_{2.5}$): Persistence and Trends in the Air Quality of Five India Cities

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Abstract: Poor air quality in India has sparked our interest in studying the time series dynamics of $PM_{2.5}$ in India's five most populous cities (Mumbai, New Delhi, Hyderabad, Chennai, and Kolkata). Daily data for the period 2014-2023 are examined in the paper. Using fractional integration methods, we analyze the persistence, seasonality, and time trends of the data. The results indicate that all series display fractional degrees of integration, being smaller than 1 and thus presenting mean reversion. Moreover, only for New Dehli and Kolkata the time trends are significantly negative, implying a continuous reduction in the level of pollution. These findings suggest that targeted interventions, such as stricter emission regulations, improved urban planning, and the promotion of clean technologies, are essential to sustain and amplify the observed improvements in air quality. The study also highlights the need for consistent and long-term efforts to address pollution in Mumbai, Hyderabad, and Chennai, where no significant reductions have been observed, emphasizing the importance of adapting policies to regional conditions. The paper's findings can serve as a guide for air pollution management and for policymakers at the Central Pollution Control Board (CPCB) the governmental body responsible for monitoring and regulating environmental pollution in India.

Keywords: Air quality; time trends; long memory; fractional integration; seasonality

JEL Classification: C22; Q53; Q58

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1. Introduction

According to the HEI 2022 report, New Delhi and Kolkata are the most polluted cities in the world, ranking first in terms of fine particulate matter ($PM_{2.5}$) levels. In 2021 the World Air Quality Report (WHO, 2021) listed New Delhi as the capital with the most polluted air for the fourth year in a row despite the government launching the National Clean Air Programme (NCAP) in 2019 to reduce particulate matter levels by 20-30% by 2024.

Breathing air with dangerous levels of $PM_{2.5}$ causes approximately four million premature deaths each year worldwide and of these 25% of deaths occur in India (Chafe et al., 2021). The average annual levels of $PM_{2.5}$ in an area should not exceed 40 µg/m3, according to the Central Pollution Control Board (CPCB), which is India's main body for pollution control; this figure is far from that recommended by the World Health Organization (WHO), which has set the limit of 5 µg/m3 (WHO, 2021)

The average $PM_{2.5}$ concentration in India, measured in micrograms per cubic meter (µg/m3), in 2022 was 53.3, compared to the WHO's recommended annual guideline level of 5 µg/m3 (HEI, 2022). IQAir (2022) have developed a cost estimator that calculates the health and economic costs of air pollution in some of the world's largest cities; it is based on an algorithm that combines real-time data from ground-level air quality sensors ($PM_{2.5}$ and NO_2), This study provided an alarming estimate of the cost of air pollution for the world's five most populous cities (Tokyo, Delphi, Shanghai, Brazil, and Mexico City) for the entire year 2020 in terms of lives and productivity lost. In these five cities

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alone, air pollution caused nearly 200,000 deaths and cost $106 billion during 2020. Rao et al. (2021) point out that 20-50% of pollutants in the air originate from the combustion of residential solid fuels in India. Despite the Indian government's initiatives to promote the use of liquefied petroleum gas, about 70% of the Indian population still relies on solid fuels for cooking.

Another major driver of air pollution in India comes from the burning of cow dung and municipal solid waste (Stewart et al., 2021). Chakrabarti et al. (2019) estimated the health and economic costs of burning agricultural crop residues in northern India, pointing to the need for investment and alternative solutions for crop residue disposal and for this to translate into economic benefits. Cusworth et al. (2018) using a combination of observed and modelled variables, including surface measurements of $PM_{2.5}$, quantified the influence of agricultural fire emissions on air pollution in Delhi, underlining the potential health benefits of changes in agricultural practices to reduce fires. A study by the World Bank (The World Bank, 2022) revealed that a 20% decrease in $PM_{2.5}$ is associated with a 16% increase in the employment growth rate and a 33% increase in labor productivity. In its report, the World Bank estimated that the cost of health damage caused by air pollution amounted to $8.1 trillion annually, or 6.1% of global GDP.

This study focuses on the analysis of the statistical properties of $PM_{2.5}$ in cities in India during the period 2014-2023, with daily data. The choice of Mumbai, New Delhi, Hyderabad, Chennai and Kolkata as the object of analysis is based on two key criteria. First, these cities are the most populous in India, according to the 2011 census, and represent areas of high industrial, vehicular and economic activity. Their inclusion ensures that the findings are relevant to highly dynamic and densely populated urban contexts, which are major contributors to air pollution. Second, these cities have complete PM2.5 daily data series for the period 2014-2023, ensuring the consistency and quality of the results.

The selection also responds to their strategic importance in the implementation of air quality policies, as they are indicators of compliance with the National Clean Air Program (NCAP, 2019) with the reduction of particulate matter levels by 20-30% by 2024, as it allows us to know whether the effects of PM 2.5 pollution shocks are transient or permanent. In addition, the climatic and geographic diversity of these cities allows for a comprehensive analysis that considers different environmental conditions and pollution patterns, providing a robust and representative perspective of air quality dynamics in India.

For the analysis, we use fractional integration, an advanced statistical technique that allows us to characterize the long-term memory properties of the time series. This approach not only identifies the persistence of the data, but also assesses the reversion to the mean and quantifies the degree of persistence of disturbances offering greater accuracy in detecting underlying patterns when modeling complex phenomena such as air pollution, thus providing a solid basis for the formulation of policies and mitigation strategies.

The rest of the paper is structured as follows: Section 2 contains a literature review; Section 3 describes the data used in the analysis; Section 4 presents the methodology and the empirical findings, while Section 5 concludes the paper.

2. Literature Review

Studies on air pollution are numerous; some focus on health effects (Smith et al., 2000; Balakrishnan et al., 2018; Yun et al., 2022, Jianxiang et al., 2022; etc.); others look at the causes of air pollution (Badami, 2005, Puthussery et al., 2022; Ravindra et al., 2023) and the costs of pollution (Cropper et al., 2019; Pandey et al., 2021).

ARIMA (AutoRegressive Integrated Moving Average) models have been a traditional tool in time series analysis related to air quality. Previous studies, such as those by Naveen (2017) and Abhilash et al. (2018), have applied this approach to model and predict the concentration of air pollutants in regions of India. For example, Naveen (2017) used ARIMA and SARIMA models to analyze data in Kerala, concluding that these techniques provide high accuracy in short-term

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forecasting. On the other hand, Abhilash et al. (2018) integrated NO_2, PM_{10}, and SO_2 data in Bangalore, demonstrating that ARIMA effectively captures local trends and seasonalities.

Furthermore, Gopu et al. (2021) and Kulkarni et al. (2018) extended the use of ARIMA to air pollution time series analysis in Hyderabad and Nanded, respectively, showing that this approach is capable of identifying specific emission and dispersion patterns in urban regions. Chaudhuri et al. (2014), on the other hand, applied ARIMA to detect trends in pollutants and meteorological parameters in Kolkata, highlighting its usefulness in contexts where time series present marked seasonalities.

Our study focuses on another branch focused on modelling and analysing time series of air pollutants, in this case $PM_{2.5}$, in five of the most populous cities in India (Mumbai, New Delphi, Hyderabad, Chennai and Kokalta) for the time period 2014-2023, with daily observations and using a fractional integration framework; this approach is broader than the standard approach, based on stationary I(0) (e.g., ARMA) and non-stationary I(1) (ARIMA), used in most air pollution studies. The analyzed $PM_{2.5}$ series are characterized by a long memory with integration orders in the interval (0, 1), which allows us to study the reversion to the mean and whether the shocks have permanent or transient effects (Gil Alana et al., 2020 a,b; Guan-Yu et al., 2022; Mei et al., 2023; etc.).

This methodological advance is crucial for understanding pollution dynamics in cities such as Mumbai and Kolkata, where the trends detected reflect both public policy impacts and specific environmental conditions. Comparing our approach with previous studies highlights how fractional integration not only allows capturing reversion to the mean but also identifies shocks that have deeper implications in the formulation of pollution mitigation and control strategies.

Zhongfei et al. (2016) analyzed pollution in four Chinese cities between 2013 and 2015 using fractional integration methods, revealing persistent behavior in pollution levels, underscoring the need for sustained interventions to achieve long-term improvements. This study set an important precedent by highlighting that shocks to pollution levels can have long-lasting effects in the absence of appropriate policies.

For their part, Caporale et al. (2021) applied the same methodology to ten European capitals, managing to demonstrate not only reversion to the mean in PM_{10} concentrations, but also that the observed perturbations have no permanent effects. This finding has significant implications for European air quality policies, as it underlines the effectiveness of current interventions in reducing air pollutants. Finally, Gil-Alana et al. (2020a) analyzed air pollution in London, addressing seven different pollutants and finding consistent patterns of persistence. This study provides further validation of the utility of fractional integration methods for understanding underlying dynamics in complex urban contexts, highlighting the need to maintain consistent pollution control efforts to avoid setbacks.

3. Data

$PM_{2.5}$ data has been extracted from the World Air Quality Index (WAQI) in https://aqicn.org/map/world/es/. The data has been converted using the U.S. EPA (United States Environmental Protection Agency) standard. WAQI data comes from the following original sources: US. Embassy & Consulates in India.

The air quality data collected is translated into actionable insights using the U.S. Environmental Protection Agency's (EPA) NowCast algorithm. This algorithm converts raw $PM_{2.5}$ readings into an air quality index (AQI) value that can help inform health-related decisions. The index is calculated based on data from a period of 3 to 12 hours, depending on the variability of particulate matter concentration (US. Embassy & Consulates).

The series analyzed correspond to the daily data, between December 10, 2014 and September 16, 2023, of $PM_{2.5}$ (μg/m3) in Mumbai (The U.S. Consulate General's air pollution monitor covers the area of Bandra), New Delphi (The U.S. Embassy's air pollution monitor covers the Chanakyapuri area), Hyderabad (The U.S. Consulate General's Air Pollution Monitor covers the Secundarad area), Chennai (The U.S. Consulate General's Air Pollution Monitor covers the Gopalapurum area), and

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Kokalta (The U.S. Consulate General's Air Pollution Monitor covers the Park Street area). The cities have been chosen for two main reasons: on the one hand, they are the most populous cities in India according to the last census in 2011 and, on the other hand, the series of $PM_{2.5}$ values was complete.

4. Methodology and Empirical Results

As earlier mentioned, we use a time series technique denominated fractional integration that is characterized because the number of differences required in the series to render it stationary I(0) may be a fractional value. Having said this, we define the concept of integration of order 0 or I(0), also named short memory. A covariance stationary process, x(t), with mean μ is short memory or I(0) if the infinite sum of the autocovariances, defined as $\gamma(u) = E[(x(t) - \mu)(x(t+u) - \mu)]$, is finite, that is,

$$\sum_{j=-\infty}^{\infty} |\gamma(u)| < \infty. \tag{1}$$

Short memory processes can encompass the classical AutoRegressive Moving Average (ARMA) processes; however, the data may display much higher time dependence, for instance, in the case where first differences are required, as in the ARIMA models. Specifically, if first differences follow an ARMA (p, q) pattern, then the original series is denominated ARIMA (p, 1, q). These two representations, ARMA and ARIMA have been widely used in the literature to describe respectively stationary and nonstationary processes. However, it is a well-known stylized fact that may series, particular those related with natural phenomena, may display a degree of time dependence smaller than the one obtained with first integration, and this is the case of fractional integration or fractional differentiation.

A process is said to be I(d) or integrated of order d, if it admits the following representation,

$$(1 - L)^d \; x(t) \;= u(t) \;\; t = 0, \pm 1, ... \tag{2}$$

where L refers to the lag operator, i.e., Lx(t) = x(t.-1), and d is a fractional value. In this context, if d is positive, the infinite sum of autocorrelations becomes unbounded, i.e.,

$$\sum_{j=-\infty}^{\infty} |\gamma(u)| = \infty. \tag{3}$$

Several values of d are relevant for our purposes: Thus, d = 0 is relevant because it indicates short memory, while d > 0 produces long memory patterns; from a statistical viewpoint, d < 0.50 implies that the series is stationary while values of d above 0.5 produces nonstationarity; another relevant value is 1. Thus, d < 1 is associated with mean reversion, with shocks disappearing by themselves in the long run, unlike what happens with d ≥ 1, i.e., lack of mean reversion and permanency of shocks.

Following standard parameterization, we incorporate a linear time trend of the form:

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

where α and β represent coefficients that need estimation—namely, a constant and a time trend, respectively. The variable x(t) is determined by Equation (2).

In the application discussed below, our initial estimation involves a model specified by Equations (4) and (2). We assume that the error term u(t) follows a white noise process, with zero mean and constant variance. Then, autocorrelations is also permitted in u(t); however, instead of imposing a specific ARMA(p, q) model, we choose the approach developed in Bloomfield (1973) which approximates in a non-paramteric way, ARMA models with a few number of parameters. The estimation is conducted via likelihood function using its expression in the frequency domain and using Robinson's (1994) tests for the computation of the confidence intervals of the non-rejection values of d.

Tables 1 and 2 refers to the model with uncorrelated errors while Tables 3 and 4 allowing for autocorrelation in the mode of Bloomfield (1973). In all cases, the upper tables report results based on the original data, while the lower panel is associated to the results based on logarithm form. In Tables 1 and 3 we report the estimates of the differencing parameter d and their associated 95% confidence intervals for the three standard cases of i) no deterministic regressors (i.e., with no

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intercept and no time trend, results displayed in column 2), with an intercept (in column 3) and with an intercept and a time trend, i.e., using equation (1) (in column 4). In the two tables, we have marked in bold the most adequate specification for each series, based on the significance of the estimates of the deterministic terms (i.e., the constant and the time trend).

Table 1. Estimates of d and 95% confidence intervals with uncorrelated errors.

i) Original data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.73 (0.70, 0.76)	**0.71 (0.68, 0.75)**	0.71 (0.68, 0.75)
New Dehli	0.67 (0.64, 0.71)	**0.66 (0.63, 0.70)**	0.66 (0.63, 0.70)
Hyderabad	0.76 (0.72, 0.80)	**0.74 (0.71, 0.78)**	0.74 (0.71, 0.78)
Chennai	0.72 (0.68, 0.76)	**0.71 (0.67, 0.75)**	0.71 (0.67, 0.75)
Kolkata	0.76 (0.72, 0.79)	**0.75 (0.72, 0.79)**	0.75 (0.72, 0.79)
ii) Logged data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.77 (0.74, 0.81)	**0.69 (0.66, 0.73)**	0.69 (0.66, 0.73)
New Dehli	0.78 (0.75, 0.82)	**0.64 (0.62, 0.68)**	0.64 (0.62, 0.68)
Hyderabad	0.80 (0.77, 0.83)	**0.69 (0.66, 0.73)**	0.69 (0.66, 0.73)
Chennai	0.77 (0.73, 0.80)	**0.68 (0.64, 0.72)**	0.68 (0.64, 0.72)
Kolkata	0.78 (0.74, 0.82)	**0.70 (0.67, 0.74)**	0.70 (0.67, 0.74)

The values indicates the estimates of the differencing parameter d. In parenthesis, their corresponding 95% confidence intervals. In bold, the selected specification for each series.

Table 2. Estimated coefficients of the selected models. Uncorrelated errors.

i) Original data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.71 (0.68, 0.75)	173.49 (10.34)	---
New Dehli	0.66 (0.63, 0.70)	225.27 (7.32)	---
Hyderabad	0.74 (0.71, 0.78)	166.14 (10.96)	---
Chennai	0.71 (0.67, 0.75)	102.51 (6.07)	---
Kolkata	0.75 (0.72, 0.79)	281.83 (11.92)	---
i) Logged data			

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City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.69 (0.66, 0.73)	5.125 (26.73)	---
New Dehli	0.64 (0.62, 0.68)	5.376 (30.50)	---
Hyderabad	0.69 (0.66, 0.73)	5.086 (31.07)	---
Chennai	0.68 (0.64, 0.72)	4.615 (21.29)	---
Kolkata	0.70 (0.67, 0.74)	5.561 (23.31)	---

The values in column 2 are the estimated values of d, in parenthesis, their 95% confidence band. In column 3, the estimates of the intercept, in parenthesis, t-values. --- indicates statistical insignificancy.

Table 3. Estimates of d and 95% confidence intervals with autocorrelated errors.

i) Original data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.61 (0.58, 0.64)	0.59 (0.56, 0.62)	**0.59 (0.56, 0.63)**
New Dehli	0.55 (0.52, 0.58)	**0.52 (0.49, 0.56)**	0.52 (0.49, 0.56)
Hyderabad	0.63 (0.60, 0.66)	**0.60 (0.55, 0.64)**	0.60 (0.55, 0.64)
Chennai	0.51 (0.47, 0.54)	**0.46 (0.42, 0.50)**	0.46 (0.42, 0.50)
Kolkata	0.62 (0.59, 0.65)	0.60 (0.56, 0.64)	**0.60 (0.56, 0.64)**
i) Logged data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.69 (0.66, 0.72)	0.55 (0.52, 0.59)	**0.55 (0.52, 0.59)**
New Dehli	0.73 (0.68, 0.76)	**0.53 (0.50, 0.56)**	0.53 (0.50, 0.56)
Hyderabad	0.77 (0.74, 0.80)	**0.61 (0.57, 0.66)**	0.61 (0.57, 0.66)
Chennai	0.65 (0.62, 0.68)	**0.43 (0.39, 0.47)**	0.43 (0.39, 0.47)
Kolkata	0.70 (0.67, 0.74)	0.53 (0.50, 0.56)	**0.53 (0.50, 0.56)**

The values indicates the estimates of the differencing parameter d. In parenthesis, their corresponding 95% confidence intervals. In bold, the selected specification for each series.

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Table 4. Estimated coefficients of the selected models. Autocorrelated errors.

i) Original data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.59 (0.56, 0.62)	166.81 (12.02)	-0.0325 (-2.01)
New Dehli	0.52 (0.49, 0.56)	206.26 (9.82)	---
Hyderabad	0.60 (0.55, 0.64)	155.123 (12.18)	---
Chennai	0.46 (0.42, 0.50)	97.935 (11.99)	---
Kolkata	0.60 (0.56, 0.64)	248.35 (12.94)	-0.0452 (-1.91)
i) Logged data			
City	No terms	With an intercept	An intercept and a time trend
Mumbai	0.55 (0.52, 0.59)	5.071 (34.41)	-0.00035 (-2.50)
New Dehli	0.53 (0.50, 0.56)	5.268 (40.69)	---
Hyderabad	0.61 (0.57, 0.66)	5.030 (35.53)	---
Chennai	0.43 (0.39, 0.47)	4.495 (48.24)	---
Kolkata	0.53 (0.50, 0.56)	5.234 (31.14)	-0.00026 (-1.69)

The values in column 2 are the estimated values of d, in parenthesis, their 95% confidence band. In column 3, the estimates of the intercept, in parenthesis, t-values. In column 4, the time trend coefficient, in parenthesis, t-values. --- indicates statistical insignificancy.

Starting with the results based on uncorrelated u(t), (Tables 1 and 2), the first thing we observe is that the model with an intercept is the selected specification in all cases, using both original and logged data. The estimates of d are all in the interval (0, 1) supporting thus the hypothesis of fractional integration. Moreover, all values are significantly higher than 0.50 which implies that the series are nonstationary, and more importantly, all are below 1 which indicates that the series revert to the mean. The values of d range between 0.66 in the case of New Dehli and 0.75 (Kolkata) with the original data; for the logged values, the estimates range between 0.64 (New Dehli) and 0.70 (Kolkata).

If autocorrelated is permitted on u(t), we observe in Table 3 that a time trend is required in the cases of Mumbai and Kolkata. The time trend coefficient is negative in the two cases and the slope is higher in magnitude in the case of Kolkata with the original data, but in Mumbai with the logged values. Looking at the estimated values of d, they are smaller than with the case of uncorrelated errors. The lowest estimate of d takes place at Chennai with a value of d of 0.46 for the original data, and 0.43 for the logged values. The highest values are obtained at Kolkata (d = 0.60) and Mumbai (0.59) with the original data, and Kolkata (0.55) with the logged form. As with the uncorrelated results, mean reversion takes place in all cases.

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5. Conclusions

This paper contributes to the air pollution literature by using fractional integration to analyse the behavior of $PM_{2.5}$ in the five most populated cities of India: Mumbai, New Delhi, Hyderabad, Chennai, and Kolkata. Daily data from the World Air Quality Index (WAQI) were used between December 10, 2014, and September 16, 2023.

The results obtained allow assessing compliance with the National Clean Air Program (NCAP, 2019), which aims to reduce particulate matter levels by 20-30% by 2024. This analysis is fundamental to determine whether the effects of PM2.5 pollution impacts are transitory or permanent. In this regard, it is observed that all the values of the analysed series are significantly higher than 0.50, indicating that the series are not stationary. This could be attributed to climatic factors, seasonal human activities or recurrent events, suggesting an important influence of these factors on the evolution of pollution. However, all data are less than 1, indicating that the series tend to return to their historical mean, and that disturbances disappear on their own in the long term.

The presence of a transitory component in the disturbances implies that, even if a substantial reduction in emission levels is achieved, the authorities must implement control strategies that ensure the sustainability of such progress in the long term. Without continued and effective measures, it is likely that pollution levels will tend to return to their previous levels. Therefore, it is recommended that, in addition to current policies, additional measures be introduced, such as the promotion of cleaner technologies, the optimization of public transportation, and the implementation of stricter regulations on particulate-emitting industries.

The time trend coefficient shows negative results for Mumbai and Kolkata, indicating an improvement in air quality in both cities. This trend could be attributed to the adoption of cleaner technologies, improved urban infrastructure or changes in citizens' behaviors. In particular, Kolkata has the steepest magnitude slope with the original data, suggesting that the control measures implemented in the city have been particularly effective in reducing PM2.5 concentrations. In Mumbai, the recorded data reflect that the policies adopted have had a positive impact and that air quality has improved.

However, in the remaining three cities, additional efforts are needed to prevent a reversion to historical pollution levels. It is crucial to implement long-term policies that not only aim to reduce emissions, but also encourage structural change in urban planning, energy use and transportation, in order to ensure that air quality improvements are sustainable.

The results presented are robust to the different assumptions made about the error term. In addition, the use of other parametric and semiparametric long-memory approaches, such as the methods of Sowell (1992) or the updated version of the log-periodogram estimator of Geweke and Porter-Hudak (1983) (Kim and Phillips, 2006), yielded results consistent with those obtained in this study. For future research, it is recommended that nonlinear fractional integration approaches be explored, as they could provide even more accurate insight into the dynamics of air pollution in highly populated urban contexts.

In conclusion, while some progress in pollution reduction is evident in certain cities such as Mumbai and Calcutta, the implementation of long-term strategies is essential to ensure the sustainability of the improvements achieved. It is imperative that policies not only focus on immediate emission reductions but also include environmental management plans that promote a profound change in urban structures and citizen behavior, ensuring cleaner air for future generations.

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