Investigating the Implications of COVID-19 on PM\textsubscript{2.5} in Pakistan

Hassaan Sipra\textsuperscript{1}, Faheem Aslam\textsuperscript{2}, Jabir Hussain Syed\textsuperscript{3*}, Tahir Mumtaz Awan\textsuperscript{2}

\textsuperscript{1}Centre for Climate Research and Development, COMSATS University Park Road Tarlai Kalan, 45550 Islamabad, Pakistan
\textsuperscript{2}Department of Management Sciences, COMSATS University Park Road Tarlai Kalan, 45550 Islamabad, Pakistan
\textsuperscript{3}Department of Meteorology, COMSATS University Park Road Tarlai Kalan, 45550 Islamabad, Pakistan

ABSTRACT

There are profound impacts of Coronavirus disease-19 (COVID-19) globally, nationally and locally. To assess the impact of COVID-19 on the hourly concentrations of particulate matter < 2.5 microns (PM\textsubscript{2.5}) in Lahore and Karachi, Pakistan, this study employs multifractal analysis. Comparative analysis of high frequency (hourly) PM\textsubscript{2.5} data for both cities from February to April for 2019 and 2020 revealed inner dynamics of time series through seasonal and trend decomposition (STL) first, then multifractal detrended fluctuation analysis (MFDFA). The empirical findings confirmed existence of multifractality in hourly PM\textsubscript{2.5}. Based on multifractal properties, efficiency of Lahore declines during COVID-19. Furthermore, a varying impact of COVID-19 is found on the strength of multifractality of PM\textsubscript{2.5} under consideration. Drastic, significant change is found on the efficiency of air quality in Lahore before and during COVID-19 periods. Before COVID-19, PM\textsubscript{2.5} remains relatively efficient, while during COVID-19 period it shows high multifractality, the opposite of which is true for Karachi. However, all series exhibit anti-persistent (negatively correlated) behavior before and during COVID-19, with respect to the remainder component of PM\textsubscript{2.5} concentration. This means that when PM\textsubscript{2.5} concentration is high at a given time, in the next period, the concentration will be low. Intuitively, this is accurate, given that hourly PM\textsubscript{2.5} concentrations change with economic activity, which oscillates in daily cycles of high and low PM\textsubscript{2.5} concentrations. In Lahore significantly lower efficiency is observed during COVID-19; no conclusion on lockdown can be made. In Karachi, higher efficiency was achieved COVID-19, which was well correlated with the before COVID-19 period, implying effective lockdown policy. The confirmation and examination of multifractality in PM\textsubscript{2.5} concentrations of Lahore and Karachi presents researchers and policymakers with a distinct signature for the impact of COVID-19. It provides validation for the development of such policy evaluation tools, with reference to air quality in Pakistan.

Keywords: PM\textsubscript{2.5}, Air quality, Multifractal analysis, COVID-19, Lockdown

1 INTRODUCTION

The World Health Organization (WHO) notes that coronavirus disease 2019 (COVID-19) global confirmed cases climbed to 20,284,882, with 741,126 deaths in (296,736) in 188 countries (https://coronavirus.jhu.edu/map.html), after the viral outbreak was declared a pandemic on March 11, 2020. By that date, Wuhan city in the Hubei province of Peoples Republic of China (PRC), the epicenter of the viral outbreak, had been under quarantine for seven weeks, after the first patient developed COVID-19 symptoms (https://www.weforum.org/agenda/2020/04/coronavirus-spread-covid19-pandemic-timeline-milestones). The exponential growth in the pandemic has seen quarantines and lockdowns enforced wide and large, leading to significant global and regional economic disruptions. In line with the inverse relationship between economic activity
and air quality (Marquez and Smith, 1999), reported improvements in air quality across multiple urban centers where quarantines and lockdowns have been imposed (Abdullah et al., 2020; Cadotte, 2020; Sharma et al., 2020). The lockdowns are the “largest scale experiment ever” into global air quality, and lessons for future policy responses which must be explored (Watts and Kommenda, 2020).

In Pakistan, where the total COVID-19 cases (deaths) have now crossed 285,000 confirmed cases with more than 6,000 deaths (http://covid.gov.pk/stats/pakistan), provincial lockdowns were imposed in Punjab and Sindh on 24 March 2020, and on 15 April 2020, the federal government lifted restrictions on key industries, following implementation of standard operating procedures (SOPs) for safety according to the local newspapers. However, smart lockdowns were imposed by the end of February 2020. Preliminary satellite image assessments of NO\(_2\) showed improved air quality in Pakistan, comparing before/during the provincial lockdowns (Dahiya and Butt, 2020). The link between lockdowns and improved air quality has direct implications for policy development in Pakistan, where air quality has deteriorated significantly over the past decades, owing to rapid urbanization, industrialization, motorization, a booming population along with law enforcement of environmental standards (Colbeck et al., 2010; McNeill, 2019).

Despite legislation present at the national and provincial levels for ambient air quality standards (Sial et al., 2018; Shams and Khwaja, 2019), daily air quality exceedance thresholds are regularly crossed in multiple Pakistani cities, due to inadequate monitoring and enforcement (Sughis et al., 2012; Gupta et al., 2013; Javed et al., 2014; Shah and Arooj, 2019). The World Bank has expressed concern, noting higher echelons of Pakistan’s air pollution relative to low government effectiveness score (Sanchez-Triana et al., 2014), with Pakistan ranking within the 25\textsuperscript{th} percentile in 2018 for effective governance, illustrating weak policy implementation (Kaufmann et al., 2018). Budgetary constraints and lack of political ownership (Air quality does not feature in the Pakistan Tehreek-e-Insaaf’s (the ruling party) environment mandate nor in their Pakistan Clean Green Index for cities) by public institutions in effectively governing air quality is dependent of its nascent democratic set-up, the overwhelming strength of its interest groups and the state’s inability to develop, process and publicly disclose environmental information (Bernauer and Koubi, 2009; Bae et al., 2010).

In the face of disparate data collection and analysis prowess, innovative statistical analysis strategies can help in evaluating the changes to air quality with respect to the COVID-19 lockdown. Air quality systems are complex, stochastic in nature, and rely on various pollutants’ interactions and correlations with each other. Their sources and the physical and chemical processes occur within global and regional meteorology (Seaman, 2000; Lee et al., 2003a; Gokhale and Khare, 2007; Feng et al., 2015). The analysis of structural characteristics found within time series of air pollutants can elucidate the role of scaling in air quality (Gokhale and Khare, 2007). Short-term time series of air quality can identify such characteristics (or signals) in medium and long-term time series for air pollutants, since time series of air pollutants intrinsically characterize as having long-range dependence, fractality (self-similarity), persistence and scale-invariance (Taqqu et al., 1995; Lee, 2002; Lee et al., 2003b; Shi et al., 2009). Since the concept popularized three decades ago (Mandelbrot, 1982), studies have successfully applied fractal analysis (mono-fractality and multi-fractality) to time series of financial markets (Mandelbrot et al., 1997; Kumar and Deo, 2009; Wang et al., 2010), natural sciences (Udovichenko and Strizhak, 2002; Makowiec et al., 2009; Philippopoulos et al., 2019), behavioral sciences (Drożdż et al., 2010; Ihlen and Vereijken, 2013) and air pollutants (Lee and Lin, 2008; Meraz et al., 2015; Stan et al., 2020).

PM\(_{2.5}\) (particulate matter < 2.5 microns) is the standard air pollutant used to measure air quality impacts on health, since prolonged exposure to PM\(_{2.5}\) can lead to increased risk of respiratory ailments, heart disease and cancer (Rasheed et al., 2015; Mir et al., 2016). Given the COVID-19 scenario, assessing the multifractal characteristics of PM\(_{2.5}\) before and during the pandemic in selected cities of Pakistan can indicate effectiveness of lockdown policy provides guidance for reducing PM\(_{2.5}\) concentrations. Numerous studies have used this approach for PM\(_{2.5}\), specifically undertaking efficiency analysis using multifractal detrended fluctuation analysis (MFDFA), an extension of the DFA technique presented by (Peng et al., 1994). Fractal analysis in general uses a single scaling exponent that defines fluctuations in stationary time series; meanwhile, multifractal analysis describes dynamics of nonstationary time series by defining fluctuations through a continuous spectrum of exponents that highlights variations in scale.
Multifractality in PM$_{2.5}$ time series is confirmed in various studies (Dong et al., 2017; Wang et al., 2020). An example can be multifractality within the time series of PM$_{2.5}$ found for Shanghai, provided an estimate for its spectral exponent and identified its major sources. (Dong et al., 2017)

Our study is distinct from previous studies and presents some advantages over existing research. First, to reveal inner dynamics, we used hourly PM$_{2.5}$ data for the two megacities of Pakistan, Karachi and Lahore, where the highest concentration of COVID-19 cases was found and strictest lockdowns were imposed, to extract useful information about the efficiency level of PM$_{2.5}$ during as compared to before COVID-19. Efficiency refers to a regression towards randomness within the long-term memory of any time series – where multifractality is richer, efficiency is reduced. This concept has been applied mainly to financial markets, testing the market efficiency hypothesis (Thompson, 2013; Aslam et al., 2020a, b). Second, we applied Seasonal and Trend Decomposition (STL) using loess to decompose the PM$_{2.5}$ time series into seasonality, trend, and remainder components because of its robustness to outliers and flexibility to handle any type of seasonality (Theodosiou, 2011; Li et al., 2014; Gong et al., 2015). Third, we use the MFDFA as a DFA generalization proposed by Kantlehhardt et al. (2002), to detect multifractal properties of PM$_{2.5}$ remainder component in Pakistan. Although, MFDFA is well-known methodology, but was rarely applied on high frequency PM$_{2.5}$ data (Shi et al., 2009; Dong et al., 2017; Osiecimka et al., 2020).

Particularly, Multifractal analysis has not been performed on any air quality dataset for Pakistani cities. There remain gaps to reveal inner dynamics of air quality before/during COVID-19. This study presents the first findings for Pakistan on the multifractal characteristics of PM$_{2.5}$ before and during COVID-19. The main findings revealed that richest multifractality was noted in Lahore during COVID-19 and Karachi had the lowest degree of dependence during COVID-19. In the case of Lahore, although a significant change is observed in the various multifractal indicators (Hurst exponent, Renyi exponent and Holder exponent) before and during COVID-19, a conclusion regarding the effectiveness of PM$_{2.5}$ concentrations with reference to lockdown cannot be drawn. In the case of Karachi, significant reduction in multifractality is observed during COVID-19, as compared to before COVID-19. Hence, it can be concluded that during COVID-19, PM$_{2.5}$ time series became more efficient. These results are valuable for researchers and policy makers in identification of scale-free signals present in PM$_{2.5}$ concentrations, how they differ before and during COVID-19, to draw implications for lockdown imposed in selected Pakistani cities. The findings further provide support for the regulators to protect citizens’ health and environmental protection mandate by detecting impact of COVID-19. It also highlights multifractal time series analyses as techniques that require greater research sustenance if policymakers are to derive usage in policy enforcement.

2 MATERIALS AND METHODS

2.1 Data Description

Lahore and Karachi are selected as the study sites as they are the only megacities in Pakistan and constitute 14% and 16% of Pakistan’s total COVID-19 cases, respectively. In general, Lahore’s air quality fares far worse than Karachi, partly due to geography. Karachi is on the coast and benefits from wind and humidity in transporting emissions. Both cities faced smart lockdown since end of February 2020, with strict enforcement of lockdowns started on 24 March 2020, through emergency declarations made at the provincial levels. On 15 April 2020, the federal government opened key industries, essentially easing lockdown. Hourly PM$_{2.5}$ data for Lahore and Karachi was collected from 1 February to 14 April 2019/2020 to characterize internal dynamics of air pollution with respect to COVID-19 lockdowns imposed in both cities, to extract useful information about the multifractal efficiency of PM$_{2.5}$, and to provide input for future policy development. By using hourly frequency, there were 24 observations a day for a total of 74 days, which finally becomes 1,776 observations (Table 1). For 2019, Karachi and Lahore data were collected from AirVisual Node monitors kept by Pakistan Air Quality Initiative, and for 2020, data was collected from the same type of monitors at the US Consulates in each city. The monitors in both cities are within a 2-km distance of each other and have a similar urban background with high traffic volume. Quality assurance was conducted on the four datasets, and...
few error values were removed. Out of 1,776 possible hourly measurements, 99% completion of data was found in Lahore in 2019 and 2020, as well as Karachi in 2020, while Karachi in 2019 had a completion rate of 95%. We chose multifractal analysis as a viable time series method as it accounts for incomplete time series data. Prior to multifractal analysis, we undertook basic statistical analysis as histogram on hourly change in PM$_{2.5}$ concentration for the study period to determine if a reduction in PM$_{2.5}$ is observed (Fig. 1).

### 2.2 Methodology

Using the Wold representation theorem (Wold, 1938), PM$_{2.5}$ can be decomposed into deterministic and stochastic (residual) components. As anticipated by (Cleveland et al., 1990), STL method was applied to isolate the stochastic component. The STL method is preferred over other decomposition techniques because of its robustness to outliers, flexibility to seasonal component fluctuations with time and ability to handle all type of data frequencies (Kavasseri and Nagarajan, 2005; Fan et al., 2019; Aslam et al., 2020b).

The hourly PM$_{2.5}$ time series is decomposed into deterministic trend ($T_i$), seasonal components ($S_i$), and stochastic remainder ($R_i$) component, according to (Shishkin, 1965; Laib et al., 2018b), i.e.:

\[
 r(t) = T_i + S_i + R_i
\]

The R package “stats” (The details can be seen at https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/stl) is required to perform the STL decomposition (Shishkin, 1965; Laib et al., 2018b). The losess window of 24 (number of PM$_{2.5}$ readings per day) is used for seasonal extraction.

Fig. 2 depicts STL decomposition of PM$_{2.5}$ for both sampled cities before and during COVID-19. The four panels show original PM$_{2.5}$ hourly change data, seasonal component, trend component and the remainder component.

According to (Laib et al., 2018b), the MFDFA is considered as one of the powerful technique to detect time series multifractality. At the same time (Wang et al., 2014) have stated that generalize Hurst exponent can estimate on the basis of Power law given the volatility function is calculated. MFDFA is an extension of DFA and this technique can observe the correlations on long-term bases in non-stationary time series data (Peng et al., 1994).

The five steps as outlined (Kantelhardt et al., 2002) and their formulae are stated as under.

The non-stationary time series is denoted by \( \{Z_{t=1},...,N\} \) and the number of observations is represented by \( N \).

The first step involves the construction of profile:

\[
 X_{(k)} = \sum_{t-1}^{k} (Z_t - \bar{Z}),
\]

where, \( k = 1, 2, 3, ..., N \) and the mean value of the series is represented by \( \bar{Z} \).

The second step involves division of the profile \( X_{(k)} \) into \( N_s = \text{int} \, N/S \) into similar length denoted by \( s \), and these segments are non-overlapping. Time series \( N_S \) length can be non-multiple of timescale \( s \) at the end of sample some parts of the profile \( X_{(k)} \) can be omitted. The omitted part of the profile \( X_{(k)} \) can be reused by repeating same process by starting it from the ending side resulting in \( 2N_s \) segments as suggested by Kantelhardt et al. (2002).

The third step involves the local trend estimation of each distinct \( 2N_s \) via least-square fit for time series. The variance is determined afterwards.
Fig. 1. Frequency distribution of PM$_{2.5}$ concentration ($\mu$g m$^{-3}$) for (1st row) Lahore before COVID-19 (left), Lahore during COVID-19 (right) and same for (2nd row) Karachi.

The fourth step involves attaining the $q^{th}$-order by calculating the average of all parts from step two.

$$F^{q} (s, v) = \frac{1}{S} \sum_{j=1}^{S} \left[ (s+1) \sum_{j=1}^{S} \left[ x_{v}(j) \right]^{q} \right]^{1/q}$$

for any real value of $q \neq 0$, while for $q = 0$ it is given by

$$F^{0} (s, v) = \exp \left\{ \frac{1}{4N} \sum_{j=1}^{N} \ln \left[ F^{2} (s, v) \right] \right\}$$
Fig. 2. Seasonal and Trend decomposition using Loess (STL) of PM$_{2.5}$. (1st row) Original daily time series (2nd row) seasonal component (3rd row) trend component (4th row) remainder.

The increasing function of $s$ represented by $F_d(s)$.

Finally, the fifth step, to compute the association among $F_d(s)$ and $s$. If $F_d(s)$ is a power law, the time series are in the log-log scale for $q$, i.e.,

$$F_d(s) \sim s^{h(q)}$$  \hspace{1cm} (7)

while at $q = 2$, MFDFA transforms into DFA and $h(2)$ becomes Hurst exponent. The Hurst exponent has been utilized in a few time series of air pollutants (Windsor and Toumi, 2001). If $h(q) > 0.5$, the $q$ fluctuation shows persistence, $h(q) < 0.5$ shows anti-persistence and when $h(q) = 0.5$ the fluctuation of $q$ exhibits random walk.
Another way to express the estimated $h(q)$ from MFDFA as a function of Renyi exponent $\tau(q)$ as postulated in Eq. (8):

$$\tau(q) = qh(q) - 1$$

(8)

Through Legendre Transformation, the relationship between $\tau(q)$ and $f(\alpha)$ can be expressed as:

$$f(\alpha) = q\alpha - \tau(q)$$

(9)

where, $\alpha$ is the Holder exponent:

$$\alpha = h_q + \frac{\gamma h_q}{\gamma_q} - \tau_q$$

(10)

Hence, the strength of multifractality is linked with higher $h(q)$ fluctuations $\Delta h = h_{q(min)} - h_{q(max)}$. Whereas $h(q)$ decreases with $q$ increases (Zunino et al., 2008), the higher the value of $\Delta h$, the higher multifractality can be observed in time series. R package “MFDFA” developed by (Laib et al., 2018a, b) (https://www.rdocumentation.org/packages/MFDFA/versions/1.1/topics/MFDFA) was used for MFDFA analysis.

3 RESULTS AND DISCUSSION

We first apply basic statistical analysis, in the form of a histogram; hourly change in PM$_{2.5}$ concentrations for Lahore and Karachi before and during COVID-19 is presented in Fig. 1. The time series frequency distributions are similarly shaped, with most values clustered between −0.1 to 0.1. Lahore during COVID-19 showed the densest variability around that range, which is validated in the summary statistics. It showed the highest skewness (19.73) and kurtosis (586.84), as compared to Lahore before COVID-19 (2.10 and 9.76, respectively). The reverse was true for Karachi before COVID-19 (3.54 and 37.14, respectively) as compared to Karachi during COVID-19 (2.86 and 23.09, respectively). Mean hourly change in PM$_{2.5}$ in Lahore was lower before COVID-19 (0.059 µg m$^{-3}$ ± 0.009 µg m$^{-3}$) as compared to during COVID-19 (0.074 µg m$^{-3}$ ± 0.016 µg m$^{-3}$), but was higher in Karachi before COVID-19 (0.029 µg m$^{-3}$ ± 0.007 µg m$^{-3}$) as compared to during COVID-19 (0.029 µg m$^{-3}$ ± 0.006 µg m$^{-3}$).

We further conducted STL decomposition to better gauge the tendency of PM$_{2.5}$ over the study period. PM$_{2.5}$ concentrations for Lahore and Karachi before and during COVID-19 are shown in Fig. 2 as Original time series of PM$_{2.5}$ change (1st row), seasonal component (2nd row), trend component (3rd row) and remainder component (4th row). Before COVID-19, Lahore presented a gradual rising trend, with a sharper increase from end of March onward. During COVID-19 in Lahore, PM$_{2.5}$ trend is flatter until end March, beyond which a sharper decreasing trend is observed. The confirmation of the primary sources of PM$_{2.5}$ in Lahore being predominantly local — specifically transport by (Shi et al., 2014), can potentially explain how the observed drastic reversal of trend in Lahore in April is partly due to economic slowdown, mostly as reduced traffic and industrial activity. Karachi trends were lower than Lahore. Karachi before COVID-19 maintained a stable trend until end March, before declining sharply in April. Karachi during COVID-19 had a decreasing trend until mid-March, followed by a rise until end March, then a decline until mid-April. Whereas Karachi based PM$_{2.5}$ source apportionment studies also indicate the significance of transportation and industrial emissions impacting PM$_{2.5}$ concentrations, greater variability in meteorological conditions (wind and humidity) may mask the trend (Mansha et al., 2012). The remainder component shows no discernible patterns and very small fluctuations around zero, upon visual inspection. Using multifractal analysis, we can identify the scale-free, self-similar characteristics of the remainder component to draw conclusions regarding the effectiveness of the COVID-19 lockdown through PM$_{2.5}$ concentrations. The same approach to wind speed, removing seasonality and trend prior to undertaking multifractal analysis on the remainder component, was applied by other researchers (Laib et al., 2018a). This approach enhances the robustness of the results and provides more insights into the inner dynamics of PM$_{2.5}$ before and during COVID-19.
Owing the nonstationary form of time series, different scaling behaviours are present in smaller and larger fluctuations of the remainder component. Exploring multifractal characteristics of PM$_{2.5}$ before and during COVID-19 for Lahore and Karachi to determine their existence, long-range dependence, strength and efficiency provide insights regarding lockdown policy effectiveness. For illustration purpose, Fig. 3(a) shows standard MFDFA results for remainder components of PM$_{2.5}$ of Lahore for 2019 (before COVID-19). Top left of Fig. 3(a) reflects the fluctuation function

![Fluctuation function](image1)

![Hurst exponent](image2)

![Mass exponent](image3)

![Multifractal spectrum](image4)

**Fig. 3.** The MFDFA results of hourly PM$_{2.5}$ time series for Lahore and Karachi during 2019 and 2020. (Top Left) Fluctuation functions for $q = -10$, $q = 0$, $q = 10$ (Top Right) Generalized Hurst exponent for each $q$. (Bottom Left) Mass exponent, $\tau(q)$. (Bottom Right) Multifractal spectrum.
log2(Fq) versus logs plot at q = −10, q = 0, and q = 10. All q’s are (least square) fitted close to a straight line; this validates the existence of a power law relationship within small (negative q) and large fluctuations (positive q) and specifies the occurrence of multifractal properties in time series (Ihlen and Vereijken, 2013). The top right of Fig. 3(a) shows generalized Hurst Exponent h(q), with q ranging from −10 to +10. It provides insight into the long-range memory inherent in PM2.5 time series, implying that upcoming PM2.5 concentrations are dependent on prior concentrations in multifractal systems. The dependence of generalized Hurst Exponent h(q) exhibits monotonic decreasing trend with q in both cities and time periods. This declining trend of generalized Hurst Exponent h(q) confirms the presence of multifractality in time fluctuations of remainder component for PM2.5. The results in Table 2 quantitatively illustrate the declining trend of generalized Hurst exponent h(q) for both cities and time periods. For the smallest fluctuations (q = −10), each time series displayed close to a random walk (h = 0.50), except Lahore during COVID-19, which displayed highly persistent behaviour (h = 0.80), as well as rapid crossover from persistent to anti-persistent behaviour at larger fluctuations, specifically from q = 0 (0.66) to q = 2 (0.45). The other time series declined more steadily throughout. Anti-persistent behaviour (negative autocorrelation) means that positive or negative change in previous periods is followed by a reverse variation in following time.

Since MF DFA = DFA at q = 2 (implying stationarity of PM2.5 time series), the Hurst Exponent h(2) shows anti-persistent behaviour for each time series, with Lahore before COVID-19 showing a stronger anti-persistent behaviour (0.30) as compared to Lahore during COVID-19 (0.45). The drastic crossover in behaviour of PM2.5 remainder component is indicative of a significant change in Lahore’s PM2.5 over the two comparative periods. Karachi before and during COVID-19 also displayed anti-persistent behaviour at h(2), 0.33 and 0.37, respectively. There is little agreement on the variation in persistent and anti-persistent behaviour of PM2.5. Studies have found persistence and anti-persistence in daily PM2.5 concentrations across various developing countries (Bhardwaj and Pruthi, 2016; Zhang et al., 2016; Lim and Min, 2019; Zhang et al., 2019). Our study adds perspective on hourly PM2.5, with anti-persistent behaviour shown in all periods.

Fig. 3(a) (bottom left) shows Renyi exponent τ(q), derived from the Hurst exponent, is nonlinear in case of multifractal series. In all cases, τ(q) exhibits an exponential shape indicating multifractality in the remainder component of PM2.5 concentrations, confirming the results of the Hurst exponent. The multifractality is most (least) apparent in Lahore (Karachi) during COVID-19, as compared to before COVID-19, based on the curvature of the q-dependent Renyi exponent for Lahore during COVID-19. Finally, the multifractal spectrum fα in Fig. 3(b) (bottom right) shows single-humped shape, approving presence of multifractality in PM2.5 time series in all cases. Lahore before COVID-19 (during COVID-19) presented asymmetric parabolic shape that is right-skewed (left-skewed), implying the dominant role of small (large) fluctuations. Karachi before and during COVID-19 presented a more symmetric parabolic shape, implying a well-distributed role of small and large fluctuations, and high correlation between time series.

Table 2. Generalized hurst exponents for PM2.5 concentrations in Lahore and Karachi for the study period and their range over q∈ (−10, 10).

| Order q | Lahore-2019 | Lahore-2020 | Karachi-2019 | Karachi-2020 |
|---------|-------------|-------------|--------------|--------------|
| −10     | 0.48        | 0.80        | 0.56         | 0.47         |
| −8      | 0.47        | 0.78        | 0.54         | 0.46         |
| −6      | 0.44        | 0.76        | 0.51         | 0.44         |
| −4      | 0.41        | 0.73        | 0.47         | 0.43         |
| −2      | 0.37        | 0.71        | 0.43         | 0.41         |
| 0       | 0.33        | 0.66        | 0.38         | 0.39         |
| 2       | 0.30        | 0.45        | 0.33         | 0.37         |
| 4       | 0.28        | 0.24        | 0.28         | 0.34         |
| 6       | 0.27        | 0.16        | 0.25         | 0.32         |
| 8       | 0.26        | 0.11        | 0.23         | 0.31         |
| 10      | 0.25        | 0.09        | 0.21         | 0.30         |
| Δh     | 0.23        | 0.71        | 0.35         | 0.17         |
| Δα     | 0.34        | 0.89        | 0.48         | 0.26         |
The width of the generalized Hurst exponents ($\Delta h$) is reported in Table 2. This range $\Delta h$ gauges the strength of multifractality. Higher the range, the more multifractality dwells in series (Kantelhardt et al., 2002). First, there is a decreasing pattern of Hurst exponents $h(q)$ in both cities before and during COVID-19 confirming multifractality in time fluctuation of remainder components (Laib et al., 2018a). Second, Lahore shows the highest multifractality with the highest width of generalized Hurst exponent ($\Delta h = 0.71$) during COVID-19. On the other hand, Karachi exhibited lowest degree of multifractality ($\Delta h = 0.17$) during COVID-19. Similar results are confirmed by changes is multifractal spectrum $\Delta \alpha$ reported in Table 2. The richer multifractality in Lahore during COVID-19 implies that significant change is observed in the fluctuations of the remainder component, as compared to before COVID-19; however, no conclusion regarding lockdown effectiveness can be made, beyond the observed significant change in multifractal characteristics. In Karachi, significant changes to the multifractal spectra follow a more conventional pattern, where the decreasing multifractality and increasing efficiency are visible. Efficiency being linked to multifractality (Anagnostidis et al., 2016), these findings suggest that the efficiency of PM$_{2.5}$ in Karachi increased during COVID-19, as compared to before COVID-19, implying that the lockdown policy was more effective in reducing PM$_{2.5}$ concentrations in Karachi. Partly, the reason may lie in the fact that Karachi benefits from the land and sea breeze phenomenon, which keeps PM$_{2.5}$ levels comparatively more efficient (Ghauri et al., 2007; Colbeck et al., 2010). The yet greater efficiency observed during COVID-19 in Karachi allows us to conclude that the lockdown was more effective there.

Beyond long-range dependence, another source of multifractality is within the fat-tailed distribution of time series, visible in the multifractal spectrum (Matia et al., 2003; Zhang et al., 2018; Wang et al., 2020). Further studies should utilize shuffling and phase-randomization to determine the contributions of these sources of multifractality.

### 4 CONCLUSIONS

This study is the first application of MFDFA to time series of PM$_{2.5}$ in Pakistan. The analysis was applied before and during COVID-19 to determine the effectiveness of provincial lockdowns imposed in Punjab and Sindh provinces, which had an impact on the air quality of the provincial capitals. Under STL analysis, Lahore before COVID-19 showed an increasing trend throughout, while Lahore during COVID-19 was more stable before a sharp decline during lockdown period, while Karachi showed a declining trend before and during COVID-19. With seasonality removed, multifractality was confirmed in the remainder components all of the time series. Lahore (Karachi) during COVID-19 displayed stronger (weaker) persistent behaviour at small fluctuations, and at larger fluctuations, all time periods showed anti-persistent behaviour, as compared to before COVID-19. No conclusion regarding Lahore lockdown policy can be drawn based on the given data. The well-correlated relationship found in Karachi before and during COVID-19, and the reduction in multifractality, provides evidence of increasing efficiency in Karachi, implying that Karachi was able to enforce its lockdown effectively. For researchers and policymakers in Pakistan, the confirmation of multifractality within PM$_{2.5}$ time series provides another opportunity to explore the effectiveness of local policies on air quality, given the identification of distinct signatures from the impact of COVID-19 lockdown in both cities. Although the dynamics of air quality are complex, this effort further illustrates the growing need for open access to data on air quality, since its analysis provides localized context for policy implementation. Multifractal analysis validates the development of such policy evaluation tools, with reference to air quality in Pakistan. Further research is proposed on annual time series of air quality, as well as identification of the sources of multifractality. A variety of multifractal techniques can be tested for air quality of Pakistan, but multifractal cross correlation analysis of other pollutants, such as PM$_{10}$, NO$_2$, NO$_x$, O$_3$ and SO$_2$, is recommended as a next step.

### ACKNOWLEDGEMENTS

The authors would like to thank the Pakistan Air Quality Initiative and the US Consulates at Lahore and Karachi for providing their PM$_{2.5}$ data for undertaking this analysis. Their open data
access policies are important for continual understanding of air quality in Pakistan.

REFERENCES

Abdullah, S., Mansor, A.A., Napi, N.N.L.M., Mansor, W.N.W., Ahmed, A.N., Ismail, M., Ramly, Z.T.A. (2020). Air quality status during 2020 Malaysia Movement Control Order (MCO) due to 2019 novel coronavirus (2019-nCoV) pandemic. Sci. Total Environ. 729, 139022. https://doi.org/10.1016/j.scitotenv.2020.139022

Anagnostidis, P., Varsakelis, C., Emmanouilides, C.J. (2016). Has the 2008 financial crisis affected stock market efficiency? The case of eurozone. Physica A 447, 116–128. https://doi.org/10.1016/j.physa.2015.12.017

Aslam, F., Latif, S., Ferreira, P. (2020a). Investigating long-range dependence of emerging asian stock markets using multifractal detrended fluctuation analysis. Symmetry 12, 1157. https://doi.org/10.3390/sym12071157

Aslam, F., Moht, W., Ferreira, P. (2020b). Evidence of intraday multifractality in european stock markets during the recent coronavirus (COVID-19) outbreak. Int. J. Financial Stud. 8, 31. https://doi.org/10.3390/ijfs8020031

Bae, H., Wilcoxen, P., Popp, D. (2010). Information disclosure policy: Do state data processing efforts help more than the information disclosure itself? J. Policy Anal. Manage. 29, 163–182. https://doi.org/10.1002/pam.20483

Bernauer, T., Koubi, V. (2009). Effects of political institutions on air quality. Ecol. Econ. 68, 1355–1365. https://doi.org/10.1016/j.ecolecon.2008.09.003

Bhardwaj, R., Pruthi, D. (2016). Predictability and wavelet analysis of air pollutants for commercial and industrial regions in Delhi. Indian J. Ind. Appl. Math 7, 165–174. https://doi.org/10.10595/1945-919x.2016.00015.3

Cadotte, M. (2020). Early evidence that COVID-19 government policies reduce urban air pollution. EarthArXiv. https://doi.org/10.31223/osf.io/nhgj3

Cleveland, R.B., Cleveland, W.S., McRae, J.E., Terpenning, I. (1990). STL: A seasonal-trend decomposition. J. Off. Stat. 6, 3–73.

Colbeck, I., Nasir, Z.A., Ali, Z. (2010). The state of ambient air quality in pakistan—A review. Environ. Sci. Pollut. Res. 17, 49–63. https://doi.org/10.1007/s11356-009-0217-2

Dahiya, S., Butt, D. (2020). Air Quality before and after national lockdown during Coronavirus disease (COVID-19) outbreak across Pakistan. Center for Research on Energy and Clean Air. https://energyandcleancar.org/air-quality-before-and-after-national-lockdown-during-corona-virus-disease-covid-19-outbreak-across-pakistan/

Dong, Q., Wang, Y., Li, P. (2017). Multifractal behavior of an air pollutant time series and the relevance to the predictability. Environ. Pollut. 222, 444–457. https://doi.org/10.1016/j.envpol.2016.11.090

Drožď, S., Kwapien, J., Oświecimka, P., Rak, R. (2009). Quantitative features of multifractal subtleties in time series. EPL 88, 60003. https://doi.org/10.1209/0295-5075/88/60003

Fan, B., Zhang, D., Li, M., Zhong, W., Zeng, Z., Ying, L., Huang, F., Cao, Y. (2019). Achieving over 16% efficiency for single-junction organic solar cells. Sci. China Chem. 62, 746–752. https://doi.org/10.1007/s11426-019-9457-5

Feng, X., Li, Q., Zhu, Y., Hou, J., Jin, L., Wang, J. (2015). Artificial neural networks forecasting of PM$_2.5$ pollution using air mass trajectory based geographic model and wavelet transformation. Atmos. Environ. 107, 118–128. https://doi.org/10.1016/j.atmosenv.2015.02.030

Ghauri, B., Lodhi, A., Mansha, M. (2007). Development of baseline (air quality) data in Pakistan. Environ. Monit. Assess. 127, 237–252. https://doi.org/10.1007/s10661-006-9276-8

Gokhale, S., Khare, M. (2007). Statistical behavior of carbon monoxide from vehicular exhausts in urban environments. Environ. Modell. Software 22, 526–535. https://doi.org/10.1016/j.envsoft.2006.02.008

Gong, J., Hu, Y., Liu, M., Bu, R., Chang, Y., Li, C., Wu, W. (2015). Characterization of air pollution index and its affecting factors in industrial urban areas in northeastern China. Pol. J. Environ. Stud. 24, 1579–1592. https://doi.org/10.15244/pjoes/37757

Gupta, P., Khan, M.N., da Silva, A., Patadia, F. (2013). MODIS aerosol optical depth observations
over urban areas in Pakistan: Quantity and quality of the data for air quality monitoring. Atmos. Pollut. Res. 4, 43–52. https://doi.org/10.5094/APR.2013.005

Ihlen, E.A., Vereijken, B. (2013). Multifractal formalisms of human behavior. Human movement science 32, 633–651. https://doi.org/10.1016/j.humov.2013.01.008

Javed, W., Murtaza, G., Ahmad, H.R., Iqbal, M.M. (2014). A preliminary assessment of air quality index (AQI) along a busy road in Faisalabad metropolitan, Pakistan. Int. J. Environ. Sci. 5, 623–633. https://doi.org/10.6088/ijes.201405100005

Kantelhardt, J.W., Zschiegner, S.A., Koscielny-Bunde, E., Havlin, S., Bunde, A., Stanley, H.E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. Physica A 316, 87–114. https://doi.org/10.1016/S0378-4371(02)01383-3

Kaufmann, D., Kraay, A., Mastruzzi, M. (2018). The worldwide governance indicators, 2018 update.

Kavasseri, R.G., Nagarajan, R. (2005). A multifractal description of wind speed records. Chaos, Solitons Fractals 24, 165–173. https://doi.org/10.1016/j.chaos.2004.09.004

Kumar, S., Deo, N. (2009). Multifractal properties of the indian financial market. Physica A 388, 1593–1602. https://doi.org/10.1016/j.physa.2008.12.017

Laib, M., Golay, J., Telesca, L., Kanevski, M. (2018a). Multifractal analysis of the time series of daily means of wind speed in complex regions. Chaos, Solitons Fractals 109, 118–127. https://doi.org/10.1016/j.chaos.2018.02.024

Laib, M., Telesca, L., Kanevski, M. (2018b). Long-range fluctuations and multifractality in connectivity density time series of a wind speed monitoring network. Chaos 28, 033108. https://doi.org/10.1063/1.5022773

Lee, C.K. (2002). Multifractal characteristics in air pollutant concentration time series. Water Air Soil Pollut. 135, 389–409. https://doi.org/10.1023/A:1014768632318

Lee, C.K., Ho, D.S., Yu, C.C., Wang, C.C. (2003a). Fractal analysis of temporal variation of air pollutant concentration by box counting. Environ. Modell. Software 18, 243–251. https://doi.org/10.1016/S1364-8152(02)00078-6

Lee, C.K., Ho, D.S., Yu, C.C., Wang, C.C., Hsiao, Y.H. (2003b). Simple multifractal cascade model for air pollutant concentration (APC) time series. Environmetrics 14, 255–269. https://doi.org/10.1002/env.584

Lee, C.K., Lin, S.C. (2008). Chaos in air pollutant concentration (APC) time series. Aerosol Air Qual. Res. 8, 381–391. https://doi.org/10.4209/aaqar.2008.09.0039

Li, L., Qian, J., Ou, C.Q., Zhou, Y.X., Guo, C., Guo, Y. (2014). Spatial and temporal analysis of air pollution index and its timescale-dependent relationship with meteorological factors in Guangzhou, China, 2001–2011. Environ. Pollut. 190, 75–81. https://doi.org/10.1016/j.envpol.2014.03.020

Lim, G., Min, S. (2019). Correlation structures of PM2.5 concentration series in the korean peninsula. Appl. Sci. 9, 5441. https://doi.org/10.3390/app9245441

Makowiec, D., Dudkowska, A., Gałąska, R., Rynkiewicz, A. (2009). Multifractal estimates of monofractality in RR-heart series in power spectrum ranges. Physica A 388, 3486–3502. https://doi.org/10.1016/j.physa.2009.05.005

Mandelbrot, B.B. (1982). The fractal geometry of Nature, WH freeman, New York, pp. 394–397.

Mandelbrot, B.B., Fisher, A.J., Calvet, L.E. (1997). A multifractal model of asset returns. Cowles Foundation Discussion Paper No. 1164, Sauder School of Business Working Paper.

Mansha, M., Ghauri, B., Rahman, S., Amman, A. (2012). Characterization and source apportionment of ambient air particulate matter (PM$_{2.5}$) in Karachi. Sci. Total Environ. 425, 176–183. https://doi.org/10.1016/j.scitotenv.2011.10.056

Marquez, L.O., Smith, N.C. (1999). A framework for linking urban form and air quality. Environ. Modell. Software 14, 541–548. https://doi.org/10.1016/s1364-8152(99)00018-3

Matia, K., Ashkenazy, Y., Stanley, H.E. (2003). Multifractal properties of price fluctuations of stocks and commodities. EPL 61, 422. https://doi.org/10.1209/epl/i2003-00194-y

McNeill, V.F. (2019). Addressing the global air pollution crisis: Chemistry’s role. Trends in Chemistry 1, 5–8. https://doi.org/10.1016/j.trechm.2019.01.005

Meraz, M., Rodriguez, E., Femat, R., Echeverria, J., Alvarez-Ramirez, J. (2015). Statistical persistence of air pollutants (O$_3$,SO$_2$, NO$_x$ and PM$_{10}$) in Mexico City. Physica A 427, 202–217. https://doi.org/10.1016/j.physa.2015.02.009
Mir, K.A., Purohit, P., Goldstein, G.A., Balasubramanian, R. (2016). Analysis of baseline and alternative air quality scenarios for Pakistan: An integrated approach. Environ. Sci. Pollut. Res. 23, 21780–21793. https://doi.org/10.1007/s11356-016-7358-x

Oswiecimka, P., Drozdz, S., Frasca, M., Gebarowski, R., Yoshimura, N., Zunino, L., Minati, L. (2020). Wavelet-based discrimination of isolated singularities masquerading as multifractals in detrended fluctuation analyses. Nonlinear Dyn. 100, 1689–1704. https://doi.org/10.1007/s11071-020-05581-y

Peng, C.K., Buldyrev, S.V., Havlin, S., Simons, M., Stanley, H.E., Goldberger, A.L. (1994). Mosaic organization of DNA nucleotides. Phys. Rev. 49, 1685. https://doi.org/10.1103/PhysRevE.49.1685

Philippopoulos, K., Kalamaras, N., Tzanis, C.G., Deligiorgi, D., Koutsogiannis, I. (2019). Multifractal detrended fluctuation analysis of temperature reanalysis data over Greece. Atmosphere 10, 336. https://doi.org/10.3390/atmos10060336

Rasheed, A., Aneja, V.P., Aiyer, A., Rafique, U. (2015). Measurement and analysis of fine particulate matter (PM$_{2.5}$) in urban areas of Pakistan. Aerosol Air Qual. Res. 15, 426–439. https://doi.org/10.4209/aaqr.2014.10.0269

Sanchez-Triana, E., Enriquez, S., Afzal, J., Nakagawa, A., Khan, A.S. (2014). Cleaning pakistan’s air: Policy options to address the cost of outdoor air pollution. The World Bank.

Seaman, N.L. (2000). Meteorological modeling for air-quality assessments. Atmos. Environ. 34, 2231–2259. https://doi.org/10.1016/S1352-2310(99)00466-5

Shah, S.I., Arooj, F. (2019). Outdoor air quality as influenced by vehicular exhaust in metropolitan city of Lahore, Pakistan. Pak. J. Sci. Ind. Res. Series A 62, 190–196.

Shams, T., Khwaja, M.A. (2019). Assessment of Pakistan National Ambient Air Quality Standards (NAAQS’s) with Selected Asian Countries and WHO. Think Asia - Sustainable Development Policy Institute.

Sharma, S., Zhang, M., Gao, J., Zhang, H., Kota, S.H. (2020). Effect of restricted emissions during COVID-19 on air quality in India. Sci. Total Environ. 728, 138878. https://doi.org/10.1016/j.scitotenv.2020.138878

Shi, K., Liu, C.Q., Ai, N.S. (2009). Monofractal and multifractal approaches in investigating temporal variation of air pollution indexes. Fractals 17, 513–521. https://doi.org/10.1142/S0218348X09004454

Shi, W., Shang, P., Wang, J., Lin, A. (2014). Multiscale multifractal detrended cross-correlation analysis of financial time series. Physica A 403, 35–44. https://doi.org/10.1016/j.physa.2014.02.023

Shishkin, N. (1965). Third international conference on atmospheric and space electricity, 1965, Elsevier Publishing Company, Montreux, Switzerland.

Sial, S.A., Zaidi, S.M.A., Taimour, S. (2018). Review of existing environmental laws and regulations in Pakistan. WWF, Pakistan.

Stan, C., Marmureanu, L., Marin, C., Cristescu, C.P. (2020). Investigation of multifractal cross-correlation surfaces of hurst exponents for some atmospheric pollutants. Physica A 545, 123799. https://doi.org/10.1016/j.physa.2019.123799

Sughis, M., Nawrot, T.S., Ihsan-ul-Haque, S., Amjad, A., Nemery, B. (2012). Blood pressure and particulate air pollution in schoolchildren of lahore, Pakistan. BMC Public Health 12, 378. https://doi.org/10.1186/1471-2458-12-378

Taquu, M.S., Teverovsky, V., Willinger, W. (1995). Estimators for long-range dependence: An empirical study. Fractals 3, 785–798. https://doi.org/10.1142/S0218348X95000692

Theodosiou, M. (2011). Forecasting monthly and quarterly time series using STL decomposition. Int. J. Forecasting 27, 1178–1195. https://doi.org/10.1016/j.ijforecast.2010.11.002

Thompson, J.R. (2013). Analysis of market returns using multifractal time series and agent-based simulation, in Industrial Engineering, North Carolina State University.

Udovichenko, V., Strizhak, P. (2002). Multifractal properties of copper sulfide film formed in self-organizing chemical system. Theor. Exp. Chem. 38, 259–262. https://doi.org/10.1023/A:1020572016637

Wang, J., Kim, J., Shao, W. (2020). Investigation of the implications of “haze special law” on air quality in south Korea. Complexity 2020, 6193016. https://doi.org/10.1155/2020/6193016

Wang, W., Liu, K., Qin, Z. (2014). International conference on informatics and semiotics in organisations, 2014, Springer, pp. 107–115.
Wang, Y., Wei, Y., Wu, C. (2010). Cross-correlations between Chinese A-share and B-share markets. Physica A 389, 5468–5478. https://doi.org/10.1016/j.physa.2010.08.029

Watts, J., Kommenda, N. (2020). Coronavirus pandemic leading to huge drop in air pollution. The Guardian 23.

Windsor, H., Toumi, R. (2001). Scaling and persistence of UK pollution. Atmos. Environ. 35, 4545–4556. https://doi.org/10.1016/S1352-2310(01)00208-4

Wold, H. (1938). A study in the analysis of stationary time series, Almqvist & Wiksell.

Zhang, C., Ni, Z., Ni, L., Li, J., Zhou, L. (2016). Asymmetrical multifractal detrending moving average analysis in time series of PM$_{2.5}$ concentration. Physica A 457, 322–330. https://doi.org/10.1016/j.physa.2016.03.072

Zhang, C., Wang, X., Chen, S., Zou, L., Zhang, X., Tang, C. (2019). A study of daily PM$_{2.5}$ concentrations in Hong Kong using the EMD-based MFDFA method. Physica A 530, 121182. https://doi.org/10.1016/j.physa.2019.121182

Zhang, J., Gao, G., Fu, B., Wang, C., Gupta, H.V., Zhang, X., Li, R. (2020a). A universal multifractal approach to assessment of spatiotemporal extreme precipitation over the Loess Plateau of China. Hydrol. Earth Syst. Sci. 24, 809–826. https://doi.org/10.5194/hess-24-809-2020

Zhang, P., Lu, S., Li, J., Chang, X., Li, J., Li, W., Chen, G., Wang, S., Feng, W. (2020b). Broad ion beam-scanning electron microscopy pore microstructure and multifractal characterization of shale oil reservoir: A case sample from Dongying Sag, Bohai Bay Basin, China. Energy Explor. Exploit. 38, 613–628. https://doi.org/10.1177%2F0144598719893126

Zhang, Q., Lu, W., Chen, S., Liang, X. (2016). Using multifractal and wavelet analyses to determine drought characteristics: A case study of Jilin province, China. Theor. Appl. Climatol. 125, 829–840. https://doi.org/10.1007/s00704-016-1781-2

Zhang, X., Zhu, Y., Yang, L. (2018). Multifractal detrended cross-correlations between Chinese stock market and three stock markets in The Belt and Road Initiative. Physica A 503, 105–115. https://doi.org/10.1016/j.physa.2018.02.195

Zunino, L., Tabak, B.M., Figliola, A., Pérez, D., Garavaglia, M., Rosso, O. (2008). A multifractal approach for stock market inefficiency. Physica A 387, 6558–6566. https://doi.org/10.1016/j.physa.2008.08.028