



## Research article

Atmospheric pollution in Chinese cities: Trends and persistence<sup>☆</sup>Guglielmo Maria Caporale<sup>a</sup>, Nieves Carmona-González<sup>b</sup>,  
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## ABSTRACT

This paper applies fractional integration to investigate the behaviour of various pollutants in seven Chinese cities. The objective is to establish if the series exhibit long memory and if time trends are statistically significant over the sample period going from January 2014 to November 2022. The results suggest that the steps recently taken by the Chinese authorities to reduce emissions and improve air quality have already had some effect: in most cases the air pollutant series are in the stationary range, with mean reversion occurring and shocks only having temporary effects, and there are significant downward trends indicating a decline over time in the degree of pollution in China. It is also interesting that in the most recent period, the Zero-Covid policy of the Chinese authorities has led to a further fall. On the whole, it would appear that the action plan adopted by the Chinese government is bringing the expected environmental benefits and therefore it is to be hoped that such policies will continue to be implemented and extended to improve air quality even further.

## 1. Introduction

According to the World Health Organisation (2021) [1], air pollution causes 4.2 million deaths each year worldwide. Among the pollutants with the greatest impact are: particulate matter (PM<sub>10</sub> and PM<sub>25</sub>), exposure to which causes cardiovascular and respiratory diseases; sulphur dioxide (SO<sub>2</sub>), generated mainly by coal combustion, which is especially dangerous when high levels of this gas and of particulate matter (PM<sub>10</sub> and PM<sub>25</sub>) are combined: nitrogen dioxide (NO<sub>2</sub>), which causes acid rain and has very harmful effects on agriculture and livestock.

China's exponential economic growth has been achieved at a high environmental cost. In 2013, the pollution level recorded an average of 52.4 (µg/m<sup>3</sup>) of PM<sub>25</sub>, ten times higher than the limit recommended by Ref. [2]. It was then that the Chinese government decided to prioritize the fight against pollution with an action plan focused primarily on controlling coal consumption, prohibiting the construction of new coal-fired plants, and investing in renewable and nuclear energy. In addition, the circulation of cars with combustion engines was restricted with daily quotas and car registration was limited. Most recently, the lockdown measures introduced

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during the Covid-19 pandemic have led to a decrease in economic activity and thus a further fall in pollution.

Research on the dynamics of air pollution is important to assess and forecast the concentration of pollutants in order for government to be able to design effective policies aimed at improving air quality. The present study analyses the statistical properties of PM<sub>10</sub>, PM<sub>25</sub>, NO<sub>2</sub> and SO<sub>2</sub> in seven Chinese cities (Shanghai, Beijing, Chongqing, Tianjin, Shenzhen, Nanjing and Xian) over the period 2014–2022 using a fractional integration framework which, unlike standard methods based on the I(0) versus I(1) dichotomy, allows for both fractional and integer degrees of differentiation. This approach provides useful information the long-memory properties of the series, the possible presence of trends and/or mean reversion, the degree of persistence and the dynamic adjustment towards the long-run equilibrium. Most importantly, it sheds light on whether the effects of shocks are transitory or permanent, which is an essential piece of information for designing effective policies to combat air pollution. More specifically, this study has two main objectives: first, to establish whether the series exhibit long memory by using fractional integration methods; second, if evidence of the former is found, to examine the presence of time trends in the context of a fractional integration model.

The layout of the paper is the following. Section 2 briefly reviews the relevant literature. Section 3 describes the data and outlines the modelling framework. Section 4 presents the results. Section 5 offers some concluding remarks.

## 2. Literature review

Numerous studies have examined the relationship between air pollution levels and health effects in China and other countries (e.g., Refs. [3–9]). This paper contributes to another branch of literature which focuses on analysing and modelling air pollutants such as particulate matter (PM<sub>25</sub>, PM<sub>10</sub>), sulphur dioxide (SO<sub>2</sub>) and nitrogen dioxide (NO<sub>2</sub>) ([10–12]). For instance, Xiang-Li et al. [13] analysed air quality in Beijing from 2014 to 2016 using a novel long short-term memory neural network extended (LSTME) model, and showed that this specification is superior to others to model time series with long-term dependence and to capture spatio-temporal correlations and improve predictions. Naveen et al. [14] estimated ARIMA and SARIMA models to study air quality in India, and found that the former outperforms the latter. Other recent papers analysing air pollution include [15–17]. However, very few papers on atmospheric pollution use fractional integration techniques as the present one does. In particular, Zhongfei et al. [18] analysed pollution in four Chinese cities from 2013 to 2015 using this approach and found a high degree of persistence. Compared to theirs, ours covers a longer period (2014–2022) and a larger number of cities (Shanghai, Beijing, Chongqing, Tianjin, Shenzhen, Nanjing and Xian), which allows us to examine more thoroughly not only the persistence, but also the effects of the stricter policies implemented from 2016 onwards. Caporale et al. [19] applied similar methods to examine the behaviour of PM<sub>10</sub> in ten European capitals and provided evidence of mean reversion, with shocks only having temporary effects. Gil-Alana et al. [20] again used the same techniques to analyse air pollution in London and found that the seven pollutants considered are persistent.

## 3. Data and time series models

We analyse the concentration of pollutants in the air using data extracted from the World Air Quality Index (WAQI) [2] at <https://aqicn.org/map/world/es/>. The data have been converted using the US EPA (United States Environmental Protection Agency) standard. More precisely, the series examined are PM<sub>25</sub> (µg/m<sup>3</sup>), PM<sub>10</sub> (µg/m<sup>3</sup>), NO<sub>2</sub> (µg/m<sup>3</sup>) and SO<sub>2</sub> (µg/m<sup>3</sup>) from seven of the most populated Chinese cities: Shanghai, Beijing, Chongqing, Tianjin, Shenzhen, Nanjing and Xian. The data we use are daily and cover the period from January 1, 2014, to November 18, 2022. They have been obtained from AQICN. org., which is a reliable and useful tool monitoring air quality worldwide, thanks to its integration of data from a wide network of official monitoring stations and verified sources, such as government agencies and academic institutions.

The WAQI data are from the following original sources: Shanghai: <https://sthj.sh.gov.cn/http://106.37.208.233:20035/emcpublish/https://china.usembassy-china.org.cn/embassy-consulates/shanghai/air-quality-monitor-stateair/> (Shanghai Environment Monitoring Center - China National Urban air quality real-time publishing platform - US Consulate Shanghai Air Quality Monitor); Beijing: <http://www.bjmecm.com.cn/> (Beijing Environmental Protection Monitoring Center); Chongqing: <http://www.cepb.gov.cn/> (Chongqing Environmental Protection Bureau (Chongqing Main Urban Area Air Quality)); Tianjin: <http://www.tjemc.org.cn/> (China National Urban air quality real-time publishing platform - Tianjin Environmental Monitoring Center); Shenzhen: <http://www.szhec.gov.cn/>, <http://meeb.sz.gov.cn/>, <http://gdee.gd.gov.cn/> (Shenzhen Environment Network - Shenzhen Environment Network - Guangdong Environmental Protection public network); Nanjing: <http://www.jshb.gov.cn/jshbw/> (Jiangsu Province PM<sub>2.5</sub> Air Monitoring Commission); Xian: <http://sthjt.shaanxi.gov.cn/>, <http://xaepb.xa.gov.cn/> (Shaanxi Provincial Environmental Protection Office - Xi'an Environmental Protection Agency).

We estimate the following econometric model:

$$y_t = \beta_0 + \beta_1 t + x_t, (1 - L)^d x_t = u_t, t = 1, 2, \dots, \quad (1)$$

where  $y_t$  stands for the series of interest, in our case, each of the pollutant for each megacity in China;  $\alpha$  and  $\beta$  denote the constant and the coefficient on a linear time trend respectively,  $L$  is the lag operator, i.e.,  $Lx_t = x_{t-1}$ , and  $u_t$  is a short-memory process which is integrated of order 0. In order to allow for some degree of (weak) dependence we assume that  $u_t$  is autocorrelated using the exponential spectral model of Bloomfield [21]. This is a non-parametric method, which does not requires specifying a functional form and is defined exclusively in terms of its spectral density function, which approximates very well the one produced by an Autoregressive (AR) structure.

Note that fractional integration allows for a greater degree of flexibility in the model, which includes the standard cases of

stationarity  $I(0)$  and nonstationary unit roots or  $I(1)$  as particular cases of interest within the fractional framework; it also allows for nonstationary behaviour with mean reversion, when the differencing parameter  $d$  is in the range  $[0.5, 1)$ .

For the estimation, we use the Whittle function in the frequency domain by implementing a testing procedure due to Robinson [22] and widely used in empirical applications of fractional integration (see, e.g., Refs. [23–25]; etc.). This method is most efficient one in the Pitman sense against local departures from the null and it yields allows confidence intervals for the values of  $d$ .

#### 4. Empirical results

Table 1 reports the estimated values of  $d$  along with the 95 % confidence intervals of the non-rejection values using Robinson’s [22] tests under three different specifications; more precisely, column 2 displays the estimates obtained under the assumption that  $\alpha$  and  $\beta$  are both equal to zero a priori, i.e., that there are no deterministic term in the model; column 3 shows the corresponding results when the model includes an intercept only (i.e., only  $\beta$  is set equal to zero a priori), while column 4 reports the estimates from a model including both an intercept and a linear time trend. The coefficients from the specification selected in each case on the basis of the statistical significance of the regressors are shown in bold.

It can be seen that in almost all cases both the intercept and the time trend are significant; the single exception is  $\text{NO}_2$  in Xian, for which only the intercept is significant.

Table 2 reports the estimated coefficients from the selected models. The values of  $d$  are all in the interval  $(0, 0.5)$ , which implies stationary long memory for all the series under examination. The corresponding confidence intervals also include values below 0.5 in the majority of cases. Only for  $\text{SO}_2$  in Tianjin and Xian in relation are some of the values above 0.5. For  $\text{PM}_{10}$  they range between 0.16 (Beijing) and 0.17 (Shanghai and Tianjin) to 0.41 in Shenzhen, and for  $\text{PM}_{25}$  from 0.10 (Beijing) to 0.141 (Chongqin). For  $\text{NO}_2$  and  $\text{SO}_2$  the values are more homogeneous across the cities, ranging from 0.20 (Beijing,  $\text{NO}_2$ ) to 0.48 (Xian,  $\text{SO}_2$ ). Concerning the time trend coefficients, negative trends are found in all cases: for  $\text{PM}_{10}$ , the biggest coefficient correspond to Xian ( $-0.02290$ ), followed by Tianjin ( $-0.01998$ ) and Nanjing ( $-0.01990$ ); for  $\text{PM}_{25}$ , the biggest values are those for Nanjing ( $-0.02608$ ), Tianjin ( $-0.02563$ ) and Chongqin ( $-0.02547$ ). In the case of  $\text{NO}_2$  and  $\text{SO}_2$  the values are generally lower, with the biggest coefficients corresponding to Shenzhen ( $-0.00564$ ,  $\text{NO}_2$ ) and Tianjin ( $-0.01465$ ,  $\text{SO}_2$ ). To sum up, the evidence reported in Tables 1 and 2 implies that most series exhibit long

**Table 1**  
Estimates of the differencing parameter.

Series (original)	No terms	An intercept	An intercept and a linear time trend
<b>PM<sub>10</sub></b>			
SHANGHAI	0.29 (0.26, 0.32)	0.21 (0.18, 0.24)	<b>0.17 (0.14, 0.21)</b>
BELJING	0.25 (0.21, 0.28)	0.19 (0.16, 0.22)	<b>0.16 (0.12, 0.20)</b>
CHONGQING	0.44 (0.40, 0.48)	0.35 (0.31, 0.39)	<b>0.35 (0.30, 0.39)</b>
TIANJIN	0.29 (0.26, 0.32)	0.22 (0.19, 0.25)	<b>0.17 (0.12, 0.21)</b>
SHENZHEN	0.48 (0.45, 0.51)	0.40 (0.37, 0.44)	<b>0.41 (0.37, 0.45)</b>
NANJING	0.37 (0.34, 0.41)	0.28 (0.26, 0.31)	<b>0.27 (0.24, 0.31)</b>
XIAN	0.34 (0.32, 0.38)	0.29 (0.26, 0.33)	<b>0.29 (0.26, 0.33)</b>
<b>PM<sub>25</sub></b>			
SHANGHAI	0.31 (0.28, 0.34)	0.23 (0.19, 0.25)	<b>0.21 (0.16, 0.24)</b>
BELJING	0.24 (0.21, 0.27)	0.16 (0.13, 0.19)	<b>0.10 (0.05, 0.13)</b>
CHONGQING	0.49 (0.46, 0.53)	0.40 (0.37, 0.44)	<b>0.41 (0.37, 0.45)</b>
TIANJIN	0.28 (0.26, 0.31)	0.18 (0.16, 0.21)	<b>0.11 (0.08, 0.15)</b>
SHENZHEN	0.48 (0.44, 0.51)	0.39 (0.36, 0.43)	<b>0.39 (0.35, 0.42)</b>
NANJING	0.38 (0.36, 0.41)	0.28 (0.26, 0.32)	<b>0.26 (0.22, 0.29)</b>
XIAN	0.41 (0.38, 0.44)	0.35 (0.32, 0.38)	<b>0.34 (0.31, 0.37)</b>
<b>NO<sub>2</sub></b>			
SHANGHAI	0.37 (0.34, 0.40)	0.33 (0.29, 0.37)	<b>0.32 (0.29, 0.36)</b>
BELJING	0.31 (0.28, 0.34)	0.24 (0.22, 0.27)	<b>0.20 (0.17, 0.24)</b>
CHONGQING	0.39 (0.36, 0.43)	0.30 (0.27, 0.35)	<b>0.28 (0.24, 0.33)</b>
TIANJIN	0.39 (0.36, 0.42)	0.33 (0.30, 0.36)	<b>0.32 (0.29, 0.35)</b>
SHENZHEN	0.37 (0.34, 0.40)	0.29 (0.26, 0.33)	<b>0.27 (0.24, 0.31)</b>
NANJING	0.38 (0.35, 0.41)	0.31 (0.28, 0.34)	<b>0.30 (0.27, 0.34)</b>
XIAN	0.39 (0.35, 0.42)	<b>0.34 (0.31, 0.38)</b>	0.34 (0.31, 0.38)
<b>SO<sub>2</sub></b>			
SHANGHAI	0.45 (0.42, 0.49)	0.40 (0.37, 0.43)	<b>0.40 (0.36, 0.43)</b>
BELJING	0.36 (0.33, 0.39)	0.32 (0.30, 0.35)	<b>0.32 (0.29, 0.35)</b>
CHONGQING	0.47 (0.44, 0.51)	0.37 (0.35, 0.40)	<b>0.38 (0.35, 0.42)</b>
TIANJIN	0.53 (0.50, 0.55)	0.45 (0.43, 0.48)	<b>0.47 (0.45, 0.51)</b>
SHENZHEN	0.46 (0.44, 0.49)	0.36 (0.34, 0.38)	<b>0.30 (0.27, 0.34)</b>
NANJING	0.46 (0.41, 0.49)	0.37 (0.35, 0.40)	<b>0.37 (0.33, 0.42)</b>
XIAN	0.52 (0.49, 0.56)	0.48 (0.45, 0.51)	<b>0.48 (0.45, 0.52)</b>

In brackets the 95 % confidence intervals. In bold the coefficients from the selected models.

**Table 2**  
Estimates of the differencing parameter.

PM <sub>10</sub>			
Series (original)	d (95 % band)	Intercept (t-value)	Time trend (t-value)
SHANGHAI	0.17 (0.14, 0.21)	57.1150 (33.05)	-0.00733 (-8.06)
BEIJING	0.16 (0.12, 0.20)	84.8698 (20.65)	-0.01268 (-5.99)
CHONGQING	0.35 (0.30, 0.39)	89.7351 (19.90)	-0.01488 (-6.03)
TIANJIN	0.17 (0.12, 0.21)	104.2458 (27.07)	-0.01998 (-9.91)
SHENZHEN	0.41 (0.37, 0.45)	84.7741 (16.82)	-0.01460 (-4.88)
NANJING	0.27 (0.24, 0.31)	103.3665 (23.29)	-0.01990 (-8.59)
XIAN	0.29 (0.26, 0.33)	132.5406 (15.98)	-0.02290 (-5.26)
PM <sub>25</sub>			
SHANGHAI	0.21 (0.16, 0.24)	122.7524 (29.09)	-0.01368 (-6.16)
BEIJING	0.10 (0.05, 0.13)	155.8180 (45.59)	-0.02450 (-13.70)
CHONGQING	0.41 (0.37, 0.45)	170.3506 (18.84)	-0.02547 (-4.76)
TIANJIN	0.11 (0.08, 0.15)	164.0128 (52.19)	-0.02563 (-15.44)
SHENZHEN	0.39 (0.35, 0.42)	141.6770 (18.00)	-0.02179 (-4.81)
NANJING	0.26 (0.22, 0.29)	161.2983 (31.40)	-0.02608 (-9.77)
XIAN	0.34 (0.31, 0.37)	182.0665 (17.67)	-0.02377 (-4.24)
NO <sub>2</sub>			
SHANGHAI	0.32 (0.29, 0.36)	25.1219 (15.09)	-0.00404 (-4.46)
BEIJING	0.20 (0.17, 0.24)	27.7491 (24.70)	-0.00489 (-8.48)
CHONGQING	0.28 (0.24, 0.33)	29.6515 (24.72)	-0.00267 (-4.27)
TIANJIN	0.32 (0.29, 0.35)	30.1383 (15.87)	-0.00542 (-5.26)
SHENZHEN	0.27 (0.24, 0.31)	32.7553 (24.77)	-0.00564 (-8.8)
NANJING	0.30 (0.27, 0.34)	31.8203 (19.47)	-0.00521 (-6.03)
XIAN	0.34 (0.31, 0.38)	23.9029 (16.16)	-
SO <sub>2</sub>			
SHANGHAI	0.40 (0.36, 0.43)	10.0719 (12.69)	-0.00282 (-5.95)
BEIJING	0.32 (0.29, 0.35)	14.3549 (11.55)	-0.00440 (-6.65)
CHONGQING	0.38 (0.35, 0.42)	20.8013 (18.56)	-0.00619 (-9.78)
TIANJIN	0.47 (0.45, 0.51)	45.0644 (14.99)	-0.01465 (-7.10)
SHENZHEN	0.30 (0.27, 0.34)	10.8917 (23.01)	-0.00298 (-11.94)
NANJING	0.37 (0.33, 0.42)	20.5965 (18.26)	-0.00629 (-9.97)
XIAN	0.48 (0.45, 0.52)	23.7084 (13.17)	-0.00690 (-5.43)

memory, with values of  $d$  in the range (0, 0.5) in all cases except for Tianjin and Xian for SO<sub>2</sub>, and also display a significant negative trend coefficient.

Next, we examine whether the Covid-19 pandemic affected the properties of the series. More precisely, we re-estimate the models for a sample ending on 31 December 2019 and for a longer one ending on November 18, 2022, the latter including the pandemic period, and then compare the corresponding estimates. The estimated coefficients are reported in Table 3. It can be seen that in the case of the longer sample the estimates of  $d$  are in the interval (0, 0.5) once again with the only exceptions of Tianjin and Xian for SO<sub>2</sub>, and the time trend is significantly negative in all cases except for NO<sub>2</sub> in Xian. Table 4 displays the values of  $d$  and  $\beta$  for the two subsamples for comparison purposes. The estimated values of  $d$  for the full sample are only slightly higher. As for the time trend, the corresponding coefficient is lower in the majority of cases for PM<sub>10</sub>, PM<sub>25</sub> and SO<sub>2</sub> but higher for NO<sub>2</sub>. This is not a surprising result, given the Zero-Covid policy and the strict lockdown measures adopted by the Chinese government throughout the pandemic – this has clearly had an impact on mobility and economic activity and thus, at least temporarily, reduced the growth rate of gas emissions polluting the air.

## 5. Conclusions

This paper contributes to the literature on air pollution by applying fractional integration methods to investigate the behaviour of various pollutants (PM<sub>10</sub>, PM<sub>25</sub>, SO<sub>2</sub> and NO<sub>2</sub>) in seven Chinese cities (Shanghai, Beijing, Chongqing, Tianjin, Shenzhen, Nanjing and Xian) using daily data over the period January 1, 2014–November 18, 2022. The chosen framework is more general than standard ones only allowing for integer degrees of differentiation and is informative about the degree of persistence of the series of interest and on the issue of whether the effects of shocks are transitory or permanent, thereby providing guidance to policy makers as to the most effective policies to combat air pollution.

The results suggest that the steps recently taken by the Chinese authorities to reduce emissions and improve air quality have already had some effect. These policies, which include stricter regulations on industrial emissions, the promotion of electric vehicles and the closure of the most polluting coal plants, have succeeded in stabilizing pollutant concentrations in a stationary range in most of the cities analysed. This stationary behaviour implies that pollution peaks tend to revert to a stable average rather than generate sustained increases, which indicates more effective air quality management. In addition, a clear downward trend in pollution levels has been identified, reflecting a continuous and sustained decrease in the emission of particulate matter and harmful gases as a result of the

**Table 3**  
Estimates of the differencing parameter. Data ending in December 2019.

PM <sub>10</sub>			
Series (original)	d (95 % band)	Intercept (t-value)	Time trend (t-value)
SHANGHAI	0.17 (0.13, 0.22)	57.0081 (27.83)	-0.00721 (-4.47)
BEIJING	0.12 (0.07, 0.16)	86.8226 (22.95)	-0.01505 (-5.18)
CHONGQING	0.32 (0.27, 0.39)	90.9524 (19.96)	-0.01903 (-5.29)
TIANJIN	0.14 (0.11, 0.19)	109.7628 (27.71)	-0.02768 (-8.90)
SHENZHEN	0.39 (0.35, 0.44)	83.2822 (16.31)	-0.01546 (-3.58)
NANJING	0.27 (0.23, 0.32)	107.8249 (19.80)	-0.02623 (-6.25)
XIAN	0.30 (0.26, 0.35)	137.8271 (13.54)	-0.02973 (-3.74)
PM <sub>25</sub>			
SHANGHAI	0.21 (0.17, 0.25)	86.8226 (22.95)	-0.01505 (-5.18)
BEIJING	0.08 (0.04, 0.13)	158.7923 (41.04)	-0.02843 (-9.49)
CHONGQING	0.39 (0.34, 0.44)	170.8021 (18.88)	-0.02991 (-3.91)
TIANJIN	0.11 (0.07, 0.15)	167.5794 (43.37)	-0.03042 (-9.98)
SHENZHEN	0.38 (0.34, 0.42)	139.3782 (17.14)	-0.01813 (-2.67)
NANJING	0.27 (0.23, 0.32)	162.4977 (25.92)	-0.02700 (-5.59)
XIAN	0.33 (0.29, 0.37)	182.2097 (16.20)	-0.02464 (-2.75)
NO <sub>2</sub>			
SHANGHAI	0.30 (0.26, 0.34)	24.2204 (13.87)	-0.00280 (-1.98)
BEIJING	0.19 (0.15, 0.23)	27.8750 (21.13)	-0.00486 (-4.84)
CHONGQING	0.26 (0.21, 0.32)	29.2520 (23.95)	-0.00175 (-1.87)
TIANJIN	0.32 (0.29, 0.36)	30.1523 (13.40)	-0.00524 (-2.88)
SHENZHEN	0.27 (0.23, 0.32)	32.9484 (21.25)	-0.00576 (-4.82)
NANJING	0.28 (0.23, 0.32)	31.0066 (18.03)	-0.00430 (-3.23)
XIAN	0.34 (0.31, 0.38)	25.3447 (15.59)	-
SO <sub>2</sub>			
SHANGHAI	0.38 (0.34, 0.42)	10.2685 (11.57)	-0.00375 (-4.91)
BEIJING	0.32 (0.29, 0.35)	16.0851 (10.41)	-0.01505 (-5.18)
CHONGQING	0.36 (0.32, 0.41)	21.8638 (17.41)	-0.00952 (-9.29)
TIANJIN	0.47 (0.44, 0.51)	47.5048 (12.77)	-0.0245 (-5.96)
SHENZHEN	0.28 (0.23, 0.33)	11.5569 (21.06)	-0.00412 (-9.71)
NANJING	0.36 (0.31, 0.42)	21.1994 (15.88)	-0.00791 (-7.26)
XIAN	0.47 (0.44, 0.51)	23.6099 (11.60)	-0.00898 (-4.47)

implementation of these policies.

A particularly relevant aspect is the influence of the Zero-Covid policy, implemented to control the spread of the coronavirus, which has had an additional impact on air quality. During periods of confinement and strict restrictions, an even more pronounced decrease in pollution levels was observed. This was due to the drastic reduction in economic activity, vehicular traffic and industrial production, resulting in lower pollutant emissions. This phenomenon underscores the direct relationship between economic activity and pollution levels, and highlights how disease control measures can have beneficial, albeit temporary, environmental side effects.

Taken together, these findings suggest that the action plan adopted by the Chinese government, which includes a combination of environmental and public health policies, is achieving the expected benefits in terms of reducing pollution and improving air quality. However, to ensure that these gains are sustained over the long term and that China can meet its international commitments, such as those set at the United Nations Climate Change Conferences in 2021 [26] in Glasgow (COP 27) and in 2022 [27] in Sharm El Sheikh (COP 27), it is essential that these policies are not only maintained but expanded. The transition to a greener, more resilient economy is critical not only for improving public health and quality of life in Chinese cities, but also for making a significant contribution to global efforts to mitigate climate change and move toward a more sustainable and equitable future for all of China's cities.

The analysis carried out in this paper could be developed in several ways. In particular, more pollutants and more cities could be considered, which would provide a more complete picture of the level of pollution across China. In addition, from a methodological point of view, bivariate fractional integration models could be estimated to examine linkages between the series. Nonlinearities and possible breaks could also be investigated in future work.

### CRedit authorship contribution statement

**Guglielmo Maria Caporale:** Writing – original draft, Resources, Data curation. **Nieves Carmona-González:** Writing – review & editing, Visualization, Resources, Project administration, Formal analysis. **Luis Alberiko Gil-Alana:** Software, Funding acquisition, Data curation.

**Table 4**  
Comparisons across samples.

PM <sub>10</sub>				
Series	d (-Dec. 2019)	d (-Nov. 2022)	β (-Dec. 2019)	β (-Nov. 2022)
SHANGHAI	0.17 (0.13, 0.22)	0.17 (0.14, 0.21)	-0.00721 (-4.47)	-0.00733 (-8.06)
BEIJING	0.12 (0.07, 0.16)	0.16 (0.12, 0.20)	-0.01505 (-5.18)	-0.01268 (-5.99)
CHONGQING	0.32 (0.27, 0.39)	0.35 (0.30, 0.39)	-0.01903 (-5.29)	-0.01488 (-6.03)
TIANJIN	0.14 (0.11, 0.19)	0.17 (0.12, 0.21)	-0.02768 (-8.90)	-0.01998 (-9.91)
SHENZHEN	0.39 (0.35, 0.44)	0.41 (0.37, 0.45)	-0.01546 (-3.58)	-0.01460 (-4.88)
NANJING	0.27 (0.23, 0.32)	0.27 (0.24, 0.31)	-0.02623 (-6.25)	-0.01990 (-8.59)
XIAN	0.30 (0.26, 0.35)	0.29 (0.26, 0.33)	-0.02973 (-3.74)	-0.02290 (-5.26)
PM <sub>25</sub>				
SHANGHAI	0.21 (0.17, 0.25)	0.21 (0.16, 0.24)	-0.01505 (-5.18)	-0.01368 (-6.16)
BEIJING	0.08 (0.04, 0.13)	0.10 (0.05, 0.13)	-0.02843 (-9.49)	-0.02450 (-13.70)
CHONGQING	0.39 (0.34, 0.44)	0.41 (0.37, 0.45)	-0.02991 (-3.91)	-0.02547 (-4.76)
TIANJIN	0.11 (0.07, 0.15)	0.11 (0.08, 0.15)	-0.03042 (-9.98)	-0.02563 (-15.44)
SHENZHEN	0.38 (0.34, 0.42)	0.39 (0.35, 0.42)	-0.01813 (-2.67)	-0.02179 (-4.81)
NANJING	0.27 (0.23, 0.32)	0.26 (0.22, 0.29)	-0.02700 (-5.59)	-0.02608 (-9.77)
XIAN	0.33 (0.29, 0.37)	0.34 (0.31, 0.37)	-0.02464 (-2.75)	-0.02377 (-4.24)
NO <sub>2</sub>				
SHANGHAI	0.30 (0.26, 0.34)	0.32 (0.29, 0.36)	-0.00280 (-1.98)	-0.00404 (-4.46)
BEIJING	0.19 (0.15, 0.23)	0.20 (0.17, 0.24)	-0.00486 (-4.84)	-0.00489 (-8.48)
CHONGQING	0.26 (0.21, 0.32)	0.28 (0.24, 0.33)	-0.00175 (-1.87)	-0.00267 (-4.27)
TIANJIN	0.32 (0.29, 0.36)	0.32 (0.29, 0.35)	-0.00524 (-2.88)	-0.00542 (-5.26)
SHENZHEN	0.27 (0.23, 0.32)	0.27 (0.24, 0.31)	-0.00576 (-4.82)	-0.00564 (-8.8)
NANJING	0.28 (0.23, 0.32)	0.30 (0.27, 0.34)	-0.00430 (-3.23)	-0.00521 (-6.03)
XIAN	0.34 (0.31, 0.38)	0.34 (0.31, 0.38)	-	-
SO <sub>2</sub>				
SHANGHAI	0.38 (0.34, 0.42)	0.40 (0.36, 0.43)	-0.00375 (-4.91)	-0.00282 (-5.95)
BEIJING	0.32 (0.29, 0.35)	0.32 (0.29, 0.35)	-0.01505 (-5.18)	-0.00440 (-6.65)
CHONGQING	0.36 (0.32, 0.41)	0.38 (0.35, 0.42)	-0.00952 (-9.29)	-0.00619 (-9.78)
TIANJIN	0.47 (0.44, 0.51)	0.47 (0.45, 0.51)	-0.02245 (-5.96)	-0.01465 (-7.10)
SHENZHEN	0.28 (0.23, 0.33)	0.30 (0.27, 0.34)	-0.00412 (-9.71)	-0.00298 (-11.94)
NANJING	0.36 (0.31, 0.42)	0.37 (0.33, 0.42)	-0.00791 (-7.26)	-0.00629 (-9.97)
XIAN	0.47 (0.44, 0.51)	0.48 (0.45, 0.52)	-0.00898 (-4.47)	-0.00690 (-5.43)

In brackets the 95 % confidence intervals.

### Declaration of competing interest

There are no competing interests with the publication of the present manuscript.

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