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Atmospheric Pollution in Chinese Cities: Trends and Persistence

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ATMOSPHERIC POLLUTION IN CHINESE CITIES:

TRENDS AND PERSISTENCE

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Abstract

This paper applies fractional integration methods to investigate the behaviour of various pollutants (PM_{10}, PM_{25}, SO_2 and NO_2) 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 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 Chinese cities. 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.

Keywords: China; pollution; trends; persistence; long-range dependence

JEL Classification: C22. Q53

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1. Introduction

According to the World Health Organisation (2021), air pollution causes 4.2 million deaths each year worldwide. Among the pollutants with the greatest impact are: particulate matter (PM_{10} and PM_{25}), exposure to which causes cardiovascular and respiratory diseases; sulphur dioxide (SO_2), generated mainly by coal combustion, which is especially dangerous when high levels of this gas and of particulate matter (PM_{10} and PM_{25}) are combined: nitrogen dioxide (NO_2), 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/m3) of PM_{25}, ten times higher than the limit recommended by the World Health Organisation (2021). 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 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_{10}, PM_{25}, NO_2 and SO_2 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.

The layout of the paper is the following. Section 2 brieflt 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. Wenhua et al., 2020; Jing-Shu et al., 2021; Tian et al., 2022; Yun et al., 2022; Jianxiang et al., 2022). This paper contributes to another branch of literature which focuses on analysing and modelling air pollutants such as particulate matter (PM_{25}, PM_{10}), sulphur dioxide (SO_2) and nitrogen dioxide (NO_2) (e.g. Guan-Yu et al., 2022; Middya et al., 2022, and Mei et al., 2023). For instance, Xiang-Li et al. (2017) 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. (2017) estimated ARIMA and SARIMA models to study air quality in India, and found that the former outperforms the latter. Zhongfei et al. (2016) analysed pollution in four Chinese cities from 2013 to 2015 using fractional integration methods and found a high degree of persistence. Caporale et al. (2021) applied similar methods to examine the behaviour of PM_{10} in ten European capitals and provided evidence of mean reversion, with shocks only having temporary effects. Gil-Alana et al. (2020) 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) 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_{25} (μg/m3), PM_{10} (μg/m3), NO_2 (μg/m3) and SO_2 (μg/m3) from seven of the most populated Chinese cities: Shanghai, Beijing, Chongqing, Tianjin, Shenzhen, Nanjing and Xian. The data are daily and cover the period from January 1, 2014 to November 18, 2022.

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.bjmemc.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 PM2.5 Air Monitoring Comission);

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:

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

where y_t stands for the series of interest, in our case, each of the pollutant for each megacity in China; α and β 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 (1973). 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.

For the estimation, we use the Whittle function in the frequency domain by implementing a testing procedure due to Robinson (1994) and widely used in empirical applications of fractional integration (see, e.g., Gil-Alana and Robinson, 1997; Gil-Alana and Henry, 2003; Abbritti et al., 2016; 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 (1994) tests under three different specifications; more precisely, column 2 displays the estimates obtained under the assumption that α and β are both equal to zero, 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 β is set equal to zero), 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 NO_2 in Xian, for which only the intercept is significant.

TABLES 1 AND 2 ABOUT HERE

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 SO_2 in Tianjin and Xian in relation are some of the values above 0.5. For PM_{10} they range between 0.16 (Beijing) and 0.17 (Shanghai and Tianjin) to 0.41 in Shenzhen, and for PM_{25} from 0.10 (Beijing) to 0.141 (Chongqin). For NO_2 and SO_2 the values are more homogeneous across the cities, ranging from 0.20 (Beijing, NO_2) to 0.48 (Xian, SO_2). Concerning the time trend coefficients, negative trends are found in all cases: for PM_{10}, the biggest coefficient correspond to Xian (-0.02290), followed by Tianjin (-0.01998) and Nanjing (-0.01990); for PM_{25}, the biggest values are those for Nanjing (-0.02608), Tianjin (-0.02563) and Chongqin (-0.02547). In the case of NO_2 and SO_2 the values are generally lower, with the biggest coefficients corresponding to Shenzhen (-0.00564, NO_2) and Tianjin (-0.01465, SO_2).

TABLES 3 AND 4 ABOUT HERE

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) and the time trend is significantly negative in all cases except for NO_2 in Xian Table 4 displays the values of d and β 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_{10}, PM_{25} and SO_2 but higher for NO_2. 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_{10}, PM_{25}, SO_2 and NO_2) 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: 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 Chinese cities. It is also interesting that in the most recent period the Zero-Covid policy adopted to eradicate the Coronavirus has led to a further fall, as one would have expected given the tight restrictions imposed on economic activity and mobility. On the whole, it would appear that the action plan adopted by the Chinese government is bringing the expected environmental benefits; therefore, it is to be hoped that such policies will continue to be implemented and extended in order to improve air quality even further and to meet the climate targets set at the United Nations Climate Change Conferences held in 2021 in Glasgow and in Sharm El Sheikh in 2022 (COP 26 and COP 27 respectively) to secure a more sustainable future.

References

Abbritti, M., L.A. Gil-Alana, Y. Lovcha and A. Moreno (2016), Term Structure Persistence, Journal of Financial Econometrics 14, 2, 331-352.

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

Gil-Alana, L.A., & Henry, B. (2003), Fractional integration and the dynamics of the UK unemployment, Oxford Bulletin of Economics and Statistics 65, 2, 221-239.

Gil-Alana, L.A., & Robinson, P.M. (1997). Testing of unit roots and other nonstationary hypothesis in macroeconomic time series, *Journal of Econometrics* 80, 2, 241-268.

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

Guan-Yu L., Yi-Ming L., Chuen-Jinn T., Chia-Ying L. (2022) Spatial-temporal characterization of air pollutants using a hybrid deep learning/Kriging model incorporated with a weather normalization technique, Atmospheric Environment 289, 119304, 352-2310, https://doi.org/10.1016/j.atmosenv.2022.119304.

Jianxiang S., Wenjia C., Xiaotong C., Xing C., Zijian Z., Zhiyuan M., Fang Y., Shaohui Z. (2022) Synergies of carbon neutrality, air pollution control, and health improvement a case study of China energy interconnection scenario, Global Energy Interconnection 5, Issue 5, 531-542. https://doi.org/10.1016/j.gloei.2022.10.007.

Jing-Shu Z., Zhao-Huan G., Zhi-Yong Z., Bo-Yi Y., Jun M., Jin Jing, Hai-Jun ., Jia-You L., Xin Zhang, C. Y. L., Hong W., Hai-Ping Z., De-Hong P., Wen-Wen B., Yu-Ming G., Ying-Hua M., Guang-Hui D., Ya-Jun C. () Long-term exposure to ambient air pollution and metabolic syndrome in children and adolescents: A national cross-sectional study in China, Environment International 148, 106383 https://doi.org/10.1016/j.envint.2021.106383

Mei C., Yongxu C., Hongyu Z., Youshuai W., Yue X. (2023) Analysis of pollutants transport in heavy air pollution processes using a new complex-network-based model, Atmospheric Environment 292, 19395, https://doi.org/10.1016/j.atmosenv.2022.119395.

Middya AI, Roy S. (2022) Pollutant specific optimal deep learning and statistical model building for air quality forecasting, Environmental Pollution 301, 118972. https://doi.org/10.1016/j.envpol.2022.118972.

Naveen V., Anu N. (2017) Time series analysis to forecast air quality indices in Thiruvananthapuram District, Kerala, India. Journal of Engineering Research and Application 7(6), 66-84. https://doi: 10.9790/9622-0706036684

Robinson, P.M. (1994) Efficient tests of nonstationary hypotheses. Journal of the American Statistical Association 89, 1420-1437.

Tian F., Hongwen C., Jianzheng L. (2022) Air pollution-induced health impacts and health economic losses in China driven by US demand exports, Journal of Environmental Management 324, 116355, https://doi.org/10.1016/j.jenvman.2022.116355.

United Nations Climate Change Conference (COP 26) (2021). https://www.un.org/en/climatechange/cop26

United Nations Climate Change Conference (COP 27) (2022). https://unfccc.int/cop27

World Air Quality Index (WAQI). https://aqicn.org/map/

Wenhua Y., Dian Caturini Sulistyoningrum, Danijela Gasevic, Rongbin Xu, Madarina Julia, Indah Kartika Murni, Zhuying Chen, Peng Lu, Yuming Guo, Shanshan Li (2020) Long-term exposure to PM2.5 and fasting plasma glucose in non-diabetic adolescents in Yogyakarta, Indonesia, Environmental Pollution 257,113423. https://doi.org/10.1016/j.envpol.2019.113423.

World Health Organization (2021). Ambient (outdoor) air pollution. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

XiangLi, LingPeng, Xiaojing Y., ShaolongCui,Y., ChengzengY. and TianheChi (2017). Long short-term memory neural network for air pollutant concentration predictions: Method development and evaluation. Environmental Pollution 231, Part 1, 997-1004. https://doi.org/10.1016/j.envpol.2017.08.114

Yun Hang, Xia Meng, Tiantian Li, Tijian Wang, Junji Cao, Qingyan Fu, Sagnik Dey, Shenshen Li, Kan Huang, Fengchao Liang, Haidong Kan, Xiaoming Shi, Yang Liu (2022) Assessment of long-term particulate nitrate air pollution and its health risk in China, iScience 25, Issue 9, 104899, https://doi.org/10.1016/j.isci.2022.104899.

Zhongfei C., Barros C.P., Gil-Alana, L.A. (2016) The persistence of air pollution in four mega-cities of China, Habitat International 56, 103-108, https://doi.org/10.1016/j.habitatint.2016.05.004.

Table 1: Estimates of the differencing parameter

PM_{10}			
Series (original)	No terms	An intercept	An intercept and a linear time trend
SHANGHAI	0.29 (0.26, 0.32)	0.21 (0.18, 0.24)	**0.17 (0.14, 0.21)**
BEIJING	0.25 (0.21, 0.28)	0.19 (0.16, 0.22)	**0.16 (0.12, 0.20)**
CHONGQING	0.44 (0.40, 0.48)	0.35 (0.31, 0.39)	**0.35 (0.30, 0.39)**
TIANJIN	0.29 (0.26, 0.32)	0.22 (0.19, 0.25)	**0.17 (0.12, 0.21)**
SHENZHEN	0.48 (0.45, 0.51)	0.40 (0.37, 0.44)	**0.41 (0.37, 0.45)**
NANJING	0.37 (0.34, 0.41)	0.28 (0.26, 0.31)	**0.27 (0.24, 0.31)**
XIAN	0.34 (0.32, 0.38)	0.29 (0.26, 0.33)	**0.29 (0.26, 0.33)**
PM25			
Series (original)	No terms	An intercept	An intercept and a linear time trend
SHANGHAI	0.31 (0.28, 0.34)	0.23 (0.19, 0.25)	**0.21 (0.16, 0.24)**
BEIJING	0.24 (0.21, 0.27)	0.16 (0.13, 0.19)	**0.10 (0.05, 0.13)**
CHONGQING	0.49 (0.46, 0.53)	0.40 (0.37, 0.44)	**0.41 (0.37, 0.45)**
TIANJIN	0.28 (0.26, 0.31)	0.18 (0.16, 0.21)	**0.11 (0.08, 0.15)**
SHENZHEN	0.48 (0.44, 0.51)	0.39 (0.36, 0.43)	**0.39 (0.35, 0.42)**
NANJING	0.38 (0.36, 0.41)	0.28 (0.26, 0.32)	**0.26 (0.22, 0.29)**
XIAN	0.41 (0.38, 0.44)	0.35 (0.32, 0.38)	**0.34 (0.31, 0.37)**
NO2			
Series (original)	No terms	An intercept	An intercept and a linear time trend
SHANGHAI	0.37 (0.34, 0.40)	0.33 (0.29, 0.37)	**0.32 (0.29, 0.36)**
BEIJING	0.31 (0.28, 0.34)	0.24 (0.22, 0.27)	**0.20 (0.17, 0.24)**
CHONGQING	0.39 (0.36, 0.43)	0.30 (0.27, 0.35)	**0.28 (0.24, 0.33)**
TIANJIN	0.39 (0.36, 0.42)	0.33 (0.30, 0.36)	**0.32 (0.29, 0.35)**
SHENZHEN	0.37 (0.34, 0.40)	0.29 (0.26, 0.33)	**0.27 (0.24, 0.31)**
NANJING	0.38 (0.35, 0.41)	0.31 (0.28, 0.34)	**0.30 (0.27, 0.34)**
XIAN	0.39 (0.35, 0.42)	**0.34 (0.31, 0.38)**	0.34 (0.31, 0.38)
SO2			
Series (original)	No terms	An intercept	An intercept and a linear time trend
SHANGHAI	0.45 (0.42, 0.49)	0.40 (0.37, 0.43)	**0.40 (0.36, 0.43)**
BEIJING	0.36 (0.33, 0.39)	0.32 (0.30, 0.35)	**0.32 (0.29, 0.35)**
CHONGQING	0.47 (0.44, 0.51)	0.37 (0.35, 0.40)	**0.38 (0.35, 0.42)**
TIANJIN	0.53 (0.50, 0.55)	0.45 (0.43, 0.48)	**0.47 (0.45, 0.51)**
SHENZHEN	0.46 (0.44, 0.49)	0.36 (0.34, 0.38)	**0.30 (0.27, 0.34)**
NANJING	0.46 (0.41, 0.49)	0.37 (0.35, 0.40)	**0.37 (0.33, 0.42)**
XIAN	0.52 (0.49, 0.56)	0.48 (0.45, 0.51)	**0.48 (0.45, 0.52)**

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

Table 2: Estimates of the differencing parameter

PM_{10}			
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_{25}			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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_2			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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.º8)
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_2			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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)

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

PM_{10}			
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_{25}			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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_2			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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_2			
Series (original)	d (95% band)	Intercept (t-value)	Time trend (t-value)
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)

Table 4: Comparisons across samples

PM_{10}				
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_{25}			
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_2			
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.º8)
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_2			
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.