Navarra Center for International Development

Working Paper nº 04/2016

THE PERSISTENCE OF AIR POLLUTION IN FOUR MEGA-CITIES OF CHINA

Carlos P. Barros
ISEG-School of Economics and management of the University of Lisbon and CESA- Research Centre on Africa, Latin America and Asia

Luis A. Gil-Alana
Navarra Center for International Development, Univeristy of Navarra

Zhongfei Chen
3. School of Economics, Jinan University

Navarra Center for International Development WP-04/2016

The persistence of air pollution in four mega-cities of China

Carlos P. Barros[1]· Luis A. Gil-Alana[2] · Zhongfei Chen[3]

1. ISEG-School of Economics and management of the University of Lisbon and CESA- Research Centre on Africa, Latin America and Asia. Email: cbarros@iseg.ulisboa.pt.
2. Faculty of Economics and I.C.S., Edificio Biblioteca, University of Navarra, Entrada Este,31080 Pamplona, Spain. Mail: alana@unav.es
3. School of Economics, Jinan University, No. 601 Huangpu West Road, Guangzhou, Guangdong Province, China. Mail: hongyeczf@163.com

Abstract: This paper analyses long range fractional dependence of China pollution in four major cities, namely Beijing, Shangai, Guangzhou and Shenzhen from September 28 of 2013 to December 12 of 2015. Unit roots hypotheses are tested by using fractional integration methods using both uncorrelated and autocorrelated errors. The results reveal that the pollution is persistent, meaning that it will continue until strong anti-pollution measures are adopted. Policy implication is derived.

Keywords: Chinese cities, pollution, unit roots, AR(1)

JEL Classification: C22; O11

Corresponding author: Prof. Luis A. Gil Alana. University of Navarra, Faculty of Economics and ICS (NCID), Edificio Amigos, Pamplona, Spain; Phone: +34 948 425 625; Fax: +34 948 425 626; Email: alana@unav.es

1. Introduction

After more than three decades of rapid development since 1978, China is nowadays experiencing very severe air pollution, especially where there is accelerating urbanization in (Zheng et al., 2015). Due to the concern regarding health effects caused by the deteriorating air quality, China's air pollution has become a hot topic for both the public and scholars (Matus et al., 2012; Chen et al., 2013; Shi et al., 2014; Feng and Liao, 2016). At present, there is little disagreement that air pollution poses a major environmental risk to human health (Tanaka, 2015; Guo et al., 2016). Moreover, the poor air quality also undermines the long-term sustainable development of China (Liu et al., 2015; Zheng et al., 2015). According to the estimation of the World Bank, the annual economic loss caused by air pollution could approach as much as 1.2% of China’s GDP (Zheng et al., 2015). The degraded air quality also plays a very significant role in causing a significant amount of immigrants to flee China. However, how to effectively reduce the air pollutants remains an important question yet to be answered.

During recent years, sharply increasing empirical research on China also verifies the conclusion on the detrimental health effects of air pollution (Almond et al., 2009; Chen et al., 2013; Tanaka, 2015). However, the existing literature rarely pays attention to the persistence of the air pollution (Liu et al., 2015), namely the time characteristics of air pollution, which will shed light on the persistence of air pollution and the differences between the different regions of China. Meanwhile, a strong understanding of the persistence will also provide important policy implications for the government authorities with regard to regulation on the emission of pollutants. Depending on the degree of persistence, including mean reverting, unit roots and long memory, different policy measures may also be adopted, and this degree of persistence is determined by the model associated to the data (Smyth, 2013; Barros et al., 2016). This is the second important motivation of our paper. To investigate the persistence of air pollutant emission in the four mega-cities of China, we adopt the innovative fractional integration and autoregressive models to analyze the time series during the period from 2013 to 2015. With allowing for fractional values, a much richer degree of flexibility in the dynamic specification of these series will be displayed.

Despite air pollution being a great threat to human health as well as to long-term development, most previous research focuses solely on certain kinds of pollution, such as particulate matter 2.5 (PM 2.5) or sulfur dioxide (SO_2), without differentiating the different kinds of air pollutants and making a systematic analysis on all of them. Furthermore, it also ignores that the dynamics of different kinds of air pollutants varies both over time and from region to region. As the air pollution levels are determined by the concentrations of a complex mixture of air pollutants, SO_2, NO_2, CO, O_3, PM2.5 and particulate matter 10 (PM10) are defined as the six criteria pollutants around the world in quantifying air pollution levels. In this paper, we will fill the gap in the existing literature and examine these different air pollutants in different regions of China, respectively[1].

The remainder of the paper is organized as follows: Section 2 introduces the background of China's air pollution in four different mega-cities in China. Section 3 presents the literature review, followed by Section 4 that introduces the methodology and models. Section 5 displays the data and empirical results and Section 6 concludes.

2. Contextual setting of China's Air Pollution

2.1 The air pollution in China

According to the National Bureau of Statistics of China (www.stats.gov.cn), the energy consumed by the whole country amounted to the equivalent of 3.84 billion tons of coal in 2014, which is as much as 6.74 times of the total energy consumption in China in 1978. Meanwhile, coal consumption reached 2.47 billion tons in 2014, which is about 6.11 times the volume of coal consumption in 1978. As China has always relied on traditional fossil fuel energy in the last three decades, it produces plenty of byproducts of "economic miracles", which are regarded as the major anthropogenic contributors to air pollution in China (Chan and Yao, 2008; Chen et al., 2013).

Although the government had promulgated the Environmental Protection Law as early as 1979 (more details can be seen in Feng and Liao (2016)), the legislation for air pollution in China has significant defects (Zhang and Wen, 2008; Wang and Hao, 2012; Feng and Liao, 2016), especially in the context of a slowdown of

[1] As the data on O_3 is unavailable, we have not make analysis on it.

economic growth. Recently, as the serious haze pollution began to blanket many Chinese cities in 2013, the government announced an unprecedentedly more restrictive standard on pollutant limits, which had previously been revised twice before in 1995 and 2000 (i.e. GB3095-1995, GB3095-2000), in order to prevent and control air pollution in China (See Table 1). Moreover, comparing to the former standards in 2000, the new Chinese National Standards for Ambient Air Quality also brought the pollutant PM2.5 into its scope. This is also much higher than the air quality standard in the Europe and United States (Wang and Hao, 2012).

[Insert Table 1 about here]

Despite there being an established system of legislation, plans and policies on air pollution in China which has played a significantly important role in controlling air quality (Wang and Hao, 2008; Feng and Liao, 2016), the air pollutants emission, including the SO_2, Soot and NO_x (Nitrogen oxides), remain at a high level, resisting any significant decline following several years of regulation (See Figure 1).

[Insert Figures 1 and 2 about here]

Moreover, Soot emissions have sharply increased since 2010, which may explain why severe smog has consistently occurred in many cities of China. Meanwhile, compared to other countries in the world, China's mean annual exposure to PM 2.5 has been much higher since 1990 (See Figure 2), increasing to more than 50 mg/m^3 since 2010 and is well above the historical level.

2.2 The development of four mega-cities in China

As is well known, Beijing, Shanghai, Guangzhou and Shenzhen are the top notable mega-cities in China (See Figure 3). They not only play the role of the engine of economic growth in China, but also have a much larger population than other cities. The GDP of Beijing, Shanghai, Guangzhou and Shenzhen reached 3.72 trillion Yuan in 2014, which is about 58.48% of the GDP of the whole country. Meanwhile, their total population was 69.64 billion in 2014. All these four cities rank among the top 30 largest cities in the world.

[Insert Figure 3 about here]

Because there are more job opportunities in mega-cities, and the average wage is also much higher than other small cities or rural areas (Harris and Todaro, 1970), many people have been pouring into the big cities like Beijing, Shanghai, Guangzhou and Shenzhen since 1978 when population migration across regions began to be allowed by the government. Nowadays, all these four mega-cities are very crowded and full of motor vehicles. For these reasons, these mega-cities are centers of human activities, and pollutants emissions congest there. Therefore, the air quality of these mega-cities is becoming very poor due to the side effects of agglomeration (Wang et al., 2010).

3. Literature Survey

The examination of the dynamic behavior of the air pollutant emissions could be useful to obtain additional information to assist in policy decision making (Barros et al., 2014). To this end a large number of studies on the persistence of air pollution have emerged in recent decades (Raga and Le Moyne, 1996; Anh and Azzi, 1997; Windsor and Toumi, 2001; Weng et al., 2008). Meanwhile, as the time series may be affected by the non-stationarities, trends and nonlinearities, which can lead to biased estimations, many innovative methods have been developed to consider these potential characteristics and improve upon the traditional models (Meraz et al., 2015). For example, Windsor and Toumi (2001) use three methods to study the statistical characteristics of UK hourly observations of ozone, PM10 and PM2.5 with Sigma-T, Hurst rescaled range and kurtosis. Meraz et al. (2015) adopt the rescaled range analysis (R/S) to investigate the statistical persistence of air pollutants in Mexico City, including the time series of hourly observations of ozone, nitrogen dioxide, sulfur dioxide and particulate matter obtained at the Mexico City downtown monitoring station from 1999-2014. Some authors argue that the detrended fluctuation analysis (DFA) presents some advantages compared to the R/S method that allows for the identification of long-term correlations in the seemingly nonstationary time series as well as spurious long-term correlations embodied in an artifact of nonstationary (Matsoukas et al., 2000; Kantelhardt et al., 2001; Lu and Xue., 2014). Therefore, the DFA method has become very popular among scholars, for example, Varotsos et al. (2005) utilize it to detect the Athens air-pollution time-series of ozone, nitrogen oxides and particulate matter obtained from 1987-2003. Chelani (2012, 2013) also applies this method to the air pollutant concentration in Delhi.

Much relevant research discusses the air pollution in other cities around the world. Meanwhile, there is a relatively large strand of the literature that focuses on air pollution within China and its influences on human health, but the existing research pays little attention to the persistence features of air pollution. Kai et al. (2008) examine the daily air pollution indices of PM10, NO_2 and SO_2 data of Shanghai using three different techniques including R/S, DFA and spectral analysis, to detect the persistence and scaling. Liu et al. (2015) uses the DFA and multifractal method to characterize the temporal fluctuations of the three pollution indices (SO_2, NO_2 and PM10) and the daily air pollution indices of Shanghai in China. Lu and Xue (2014) and Shi (2014) also applied the DFA to analyze the particulate matter from vehicle emissions at a typical traffic intersection in Hong Kong.

In contrast to the methods mentioned above which were applied to analyze the persistence or long memory of air pollution, fractional integration, which has been widely used in applied econometrics and permits us to examine the time series properties and its disaggregate components from a very general perspective, including trend I(0) stationarity, unit roots and fractional integration in a unified treatment (Barros et al., 2016), has not been used to investigate the air pollution (Gil-Alaña and Robinson, 1997, 2001; Gil-Alana, 2003; Cuñado et al., 2005; Barros et al., 2016).

4. Methodology

The methodology used in the paper is based on the concept of long memory or long range dependence characterized by the spectral density function being unbounded at a given frequency (usually 0) or alternatively, expressed in the time domain, because the infinite sum of the auto covariances is infinite. A special case of long memory is the type of fractionally integrated or I(d) processes. These processes indicate that the number of differences required to render a series stationary I(0) may be a fractional value d and this parameter is very relevant, not only because it allows a greater degree of flexibility in the dynamic specification of the series but also because it indicates if a shock in the series is going to be transitory or permanent. Formalizing it in a mathematical way, we say that a time series is said to be integrated of order d if,

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

with $x_t = 0$, $t \leq 0$, where u_t is an I(0) process, defined as a covariance stationary process with spectral density function that is positive and finite, and L is the backward shift operator ($Lx_t = x_{t-1}$). In the case of fractional d, the polynomial in the left hand side in (1) can be expanded in terms of its Binomial expansion, such that, for all real d:

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\, L + \frac{d(d-1)}{2} L^2 - \ldots,$$

and thus

$$(1-L)^d x_t = x_t - d\, x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots .$$

In this context, d plays a crucial role as an indicator of the degree of dependence in the series. Thus, the higher the value of d is, the higher the level of association is between the observations. Processes with $d > 0$ in (1) display the property of "*long memory*", so-named because of the strong degree of association between observations distant in time. These processes are also characterised by autocorrelations decaying hyperbolically at a slow rate and with a spectral density function unbounded at the origin. If $d = 0$, the series is integrated of order 0, I(0). If $0 < d < 0.5$, the series is long memory and stationary, if $d \geq 0.5$, the series is then nonstationary and if $d = 1$ the series is integrated of order 1 or I(1). It is important to note that if the time series is I(d) with $d < 1$, the series is "mean reverting", in the sense that shocks affecting the series will disappear in the long run.[1] On the contrary, if the series is I(d) with $d \geq 1$ it is not mean reverting and shocks could eventually remain in the series forever.

Several methods exist for estimating and testing the fractional differencing parameter d. Some are parametric while others are semiparametric and they can be specified in the time or in the frequency domain. In this paper, we use a parametric frequency domain Whittle estimation approach (Dahlhaus, 1989) along with a testing procedure (Robinson, 1994), which is based on the Lagrange Multiplier (LM)

[1] Some authors, e.g., Phillips and Xiao (1999) argue that in the case of d in the interval [0.5, 1) the concept of mean reversion is a misnomer given the nonstationary nature of the process.

principle and that also uses the Whittle function in the frequency domain.[2]

5. Data and Empirical Results

The data is obtained from the website: www.tianqihoubao.com/aqi. This provides the air quality data of different cities in China every day, including SO_2, NO_2, CO, O_3, PM 2.5 and PM 10. As China began to disclose the monitoring data of PM 2.5 in late 2013, the selected sample period in this paper is from September 28 of 2013 to December 12 of 2015. The summary statistics of original time series are displayed in Table 2. Moreover, as the air pollution is much more serious in large cities compared to other smaller cities due to the higher population density and agglomeration of economic activities, we selected the four mega cities, i.e. Beijing, Shanghai, Guangzhou and Shenzhen, as the sample cities in this research.

[Insert Table 2 about here]

We start the empirical analysis by considering the following model:

$$y_t = \alpha + \beta t + x_t, \qquad (1 - L)^d x_t = u_t, \qquad (2)$$

where y_t is the observed time series, α and β are coefficients referring respectively to the intercept and a linear time trend; L is the lag-operator ($Lxt = x_{t-1}$); d is the

[2] Robinson's (1994) method has the advantage that is still valid in the context of nonstationary ($d \geq 0.5$) processes.

fractional differencing parameter, and u_t is I(0) as previously defined.

In Table 3, we assume that the I(0) u_t errors are white noise, while in Table 4 we allow for some degree of autocorrelation by means of using an AR(1) process.[3] In both cases we consider the three standard cases of no regressors (α and β are assumed to be 0 a priori in (2)); an intercept (α is unknown and β is set equal to 0); and an intercept with a linear time trend (i.e., with the two parameter taken as unknown).

[Insert Table 3 about here]

The first thing that we observe is that in all cases an intercept seems to be sufficient to describe the deterministic components of the series. In fact, though not reported, the time trend coefficient (β) was found to be statistically insignificant in all cases presented. We report in the tables the estimated values of d along with their corresponding 95% confidence bands.

For the case of white noise errors (in Table 3) we observe that the estimated values of d range between 0.42 (Shanghai in case of PM 2.5) to 0.71 (Shenzhen, with PM 10 and PM 2.5) though in all cases the unit root null hypothesis (i.e. d = 1) is rejected in favour of fractional integration.

[Insert Table 4 about here]

[3] The AR(1) model is chosen because of its simplicity and its relation with the stochastic first order differential equation.

Allowing autocorrelated errors (through an AR(1) process) the values are much smaller, and all are within the stationary region, ranging from 0.09 (Beijing, PM 10) and 0.45 (Shenzhen with CO). Thus, the values are smaller than those reported in Table 3 though still significantly different from 0 and 1.

6. Concluding comments

This paper analyses the persistence of pollution in China in four mega-cities from September 28 of 2013 to December 12 of 2015. The unit roots and fractional integration hypotheses are tested first with noise disturbances and then using AR(1) disturbances. The results reveal fractional integration with orders of integration substantially different from zero and one and thus showing persistence in air pollution in the four different mega-cities of China. The fact that the orders of integration are below 1 indicates that the pollution shocks will disappear by themselves in the long run and converge to an average value over time, albeit taking a very long time to recover. Therefore, the pollution will continue unless counter measures to control it are adopted. Unlike other research on China, this paper finds evidence that the air pollution in the four mega-cities of China has not worsened in the last three years. Moreover, for different cities and different air pollutants, different policy measure should be adopted as the degree of persistence identified is distinct. The heterogeneity lies in the averaged level of air pollutants. For Beijing and Shanghai, the mean values of different air pollutants are much larger, indicating the air quality there is much worse and the d value is much smaller. Meanwhile, for Guangzhou and Shenzhen, the averaged observed value is lower and the air quality is better, the d value seems much larger, implying higher levels of persistence. This implies that more active measures are needed to offset the external shocks of air pollution in Guangzhou and Shenzhen, to maintain the high air quality there. As for Beijing and Shanghai, air pollution seems to be stationary with long memory. However, structural reform is required to reduce pollutant emissions and thus bring down the average air pollution. Further research can be extended to other cities in China, in order to confirm the present research.

References:

Almond, D., Chen, Y., Greenstone, M., & Li, H. (2009). Winter Heating or Clean Air? Unintended Impacts of China's Huai River Policy. American Economic Review, 99(2), 184-90.

Anh, V., Duc, H., & Azzi, M. (1997). Modeling anthropogenic trends in air quality data. Journal of the Air & Waste Management Association, 47(1), 66-71.

Barros, C. P., Gil-Alana, L. A., & de Gracia, F. P. (2014). Stationarity and Long Range Dependence of Carbon Dioxide Emissions: Evidence for Disaggregated Data. Environmental and Resource Economics, 1-12.

Barros, C. P., Gil-Alana, L. A., & Wanke, P. (2016). Energy production in Brazil: Empirical facts based on persistence, seasonality and breaks. Energy Economics, 54, 88-95.

Chan, C. K., & Yao, X. (2008). Air pollution in mega cities in China. Atmospheric Environment, 42(1), 1-42.

Chelani, A.B. (2012). Persistence analysis of extreme CO, NO_2 and O_3 concentrations in ambient air of Delhi. Atmospheric Research, 108, 128-134.

Chelani, A. B. (2013). Study of extreme CO, NO_2, and O_3 concentrations at a traffic site in Delhi: statistical persistence analysis and source identification. Aerosol Air Quality Res, 13, 377-384.

Chelani, A. B. (2016). Long-memory property in air pollutant concentrations. Atmospheric Research, 171, 1-4.

Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proceedings of the National Academy of Sciences, 110(32), 12936-12941.

Cuñado, J., Gil-Alana, L. A., & De Gracia, F. P. (2005). A test for rational bubbles in the NASDAQ stock index: a fractionally integrated approach. Journal of Banking and Finance, 29(10), 2633-2654.

Dahlhaus, R. (1989) Efficient parameter estimation for self-similar process, *Annals of Statistics*, 17, 1749-1766.

Fang, M., Chan, C. K., Yao, X. (2009). Managing air quality in a rapidly developing nation: China. Atmospheric Environment, 43(1), 79-86.

Feng, L., Liao, W., 2016. Legislation, plans, and policies for prevention and control ofair pollution in China: achievements, challenges, and improvements. Journal of Cleaner Production 112, 1549-1558.

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

Gil-Alana, L. A., & Robinson, P. M. (2001). Testing of seasonal fractional integration in UK and Japanese consumption and income. Journal of Applied Econometrics, 16(2), 95-114.

Gil-Alana, L. A. (2003). Testing of Fractional Cointegration in Macroeconomic Time Series. Oxford Bulletin of Economics and Statistics, 65(4), 517-529.

Guo, Y., Zeng, H., Zheng, R., Li, S., Barnett, A. G., Zhang, S., ... & Williams, G. (2016). The association between lung cancer incidence and ambient air pollution in China: A spatiotemporal analysis. Environmental Research, 144, 60-65.

Harris, J. R., & Todaro, M. P. (1970). Migration, unemployment and development: a two-sector analysis. The American Economic Review, 126-142.

Kai, S., Chun-qiong, L., Nan-shan, A., & Xiao-hong, Z. (2008). Using three methods to investigate time-scaling properties in air pollution indexes time series. Nonlinear Analysis: Real World Applications, 9(2), 693-707.

Kantelhardt, J. W., Koscielny-Bunde, E., Rego, H. H., Havlin, S., & Bunde, A. (2001). Detecting long-range correlations with detrended fluctuation analysis. Physica A: Statistical Mechanics and its Applications, 295(3), 441-454.

Liu, Z., Wang, L., & Zhu, H. (2015). A time-scaling property of air pollution indices: a case study of Shanghai, China. Atmospheric Pollution Research, 6(5), 886-892.

Lu, W. Z., & Xue, Y. (2014). Detrended fluctuation analysis of particle number concentrations on roadsides in Hong Kong. Building and Environment, 82, 580-587.

Matsoukas, C., Islam, S., & Rodriguez -Iturbe, I. (2000)
analysis of rainfall and streamflow time series. Journal of Geophysical Research: Atmospheres (1984–2012), 105(D23), 29165-29172.

Matus, K., Nam, K. M., Selin, N. E., Lamsal, L. N., Reilly, J. M., & Paltsev, S. (2012). Health damages from air pollution in China. Global Environmental Change, 22(1), 55-66.

Meraz, M., Rodriguez, E., Femat, R., Echeverria, J. C., & Alvarez-Ramirez, J. (2015). Statistical persistence of air pollutants (O 3, SO 2, NO 2 and PM 10) in Mexico City. Physica A: Statistical Mechanics and its Applications, 427, 202-217.

Phillips, P.C.B. and Z. Xiao (1999), A primer on unit root testing, Journal of Economic Surveys 12, 423-470.

Raga, G. B., & Le Moyne, L. (1996). On the nature of air pollution dynamics in Mexico City—I. Nonlinear analysis. Atmospheric Environment, 30(23), 3987-3993.

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

Shi, H., Wang, Y., Huisingh, D., Wang, J., 2014. On moving towards an ecologically sound society: with special focus on preventing future smog crises in China and globally. Journal of Cleaner Production 64, 9-12.

Shi, K. (2014). Detrended cross-correlation analysis of temperature, rainfall, PM 10 and ambient dioxins in Hong Kong. Atmospheric Environment, 97, 130-135.

Smyth, R. (2013). Are fluctuations in energy variables permanent or transitory? A survey of the literature on the integration properties of energy consumption and production. Applied Energy, 104, 371-378.

Tanaka, S. (2015). Environmental regulations on air pollution in China and their impact on infant mortality. Journal of Health Economics, 42, 90-103.

Varotsos, C., Ondov, J., & Efstathiou, M. (2005). Scaling properties of air pollution in

Athens, Greece and Baltimore, Maryland. Atmospheric Environment, 39(22), 4041-4047.

Wang, S., & Hao, J. (2012). Air quality management in China: Issues, challenges, and options. Journal of Environmental Sciences, 24(1), 2-13.

Wang, H., Fu, L., Zhou, Y., Du, X., & Ge, W. (2010). Trends in vehicular emissions in China's mega cities from 1995 to 2005. Environmental Pollution, 158(2), 394-400.

Weng, Y. C., Chang, N. B., & Lee, T. Y. (2008). Nonlinear time series analysis of ground-level ozone dynamics in Southern Taiwan. Journal of Environmental Management, 87(3), 405-414.

Windsor, H. L., & Toumi, R. (2001). Scaling and persistence of UK pollution. Atmospheric Environment, 35(27), 4545-4556.

Zhang, K. M., & Wen, Z. G. (2008). Review and challenges of policies of environmental protection and sustainable development in China. Journal of environmental management, 88(4), 1249-1261.

Zheng, S., Yi, H., & Li, H. (2015). The impacts of provincial energy and environmental policies on air pollution control in China. Renewable and Sustainable Energy Reviews, 49, 386-394.

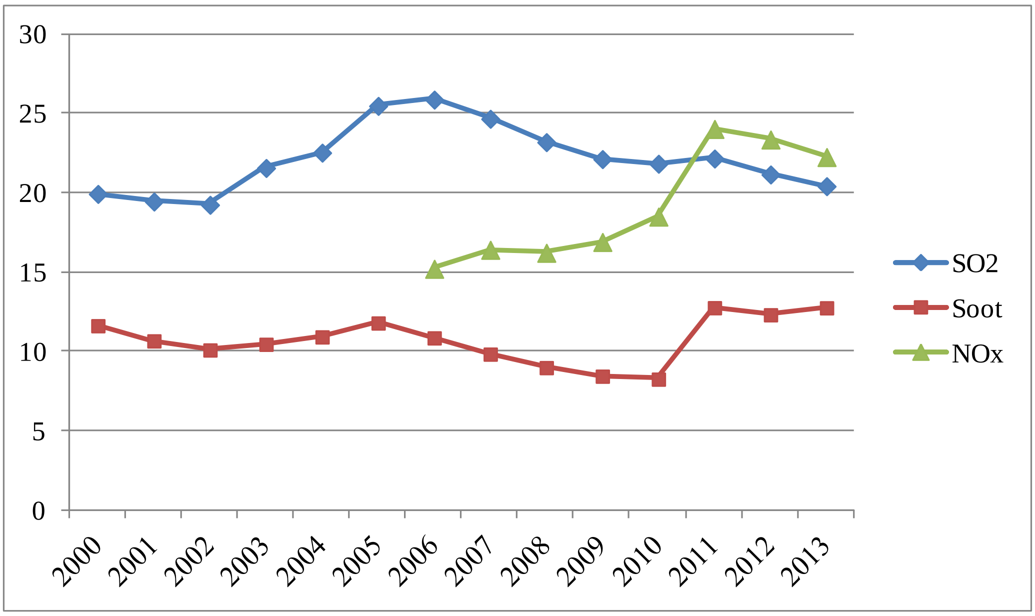

Figure 1: the SO_2, Soot and NO_x emissions in China during 2000-2013 (unit: billion tons).

Sources: China statistical yearbook on environment

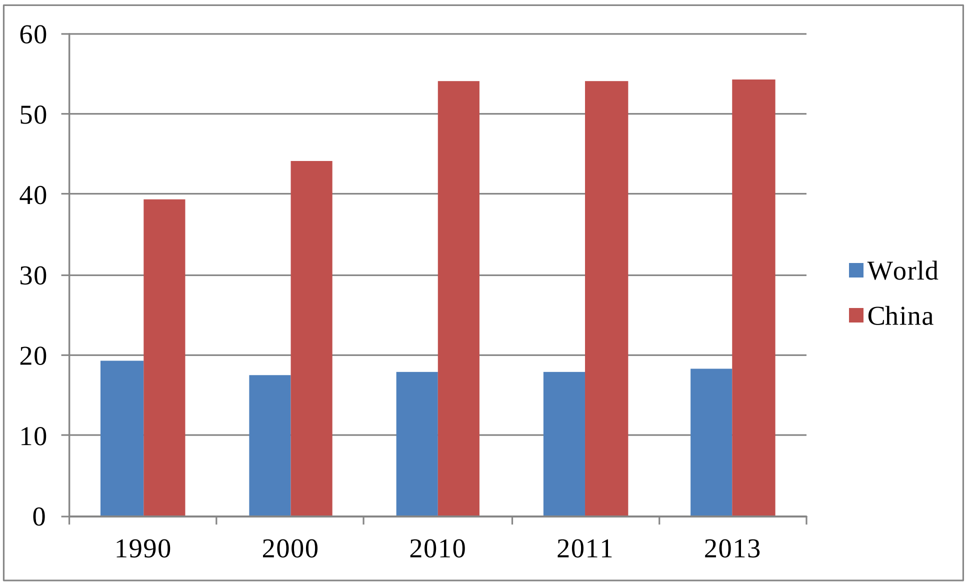

Figure 2: The mean annual exposure of the PM 2.5 in China and World (unit: mg/m^3)

Sources: The World Bank Database.

Figure 3: The map of four mega-cities in China

Table 1: Concentration limits for basic pollutants in the Chinese National Standards for Ambient Air Quality "GB3095-2012"(unit: mg/m^3)

Pollutant	Frequency	Grade-I	Grade-II
SO_2	Daily	0.05	0.15
	Annual	0.02	0.06
NO_2	Daily	0.08	0.08
	Annual	0.04	0.04
CO	Daily	4	4
	Hourly	10	10
O_3	Daily	0.1	0.16
	Hourly	0.16	0.2
PM 10	Daily	0.05	0.15
	Annual	0.04	0.07
PM 2.5	Daily	0.035	0.075
	Annual	0.015	0.035

Table 2: The summery statistics of the air pollutant in four mega-cities

	Variable	Obs	Mean	Std. Dev.	Min	Max
Beijing	CO	784	1.25	0.94	0.22	8.11
	NO_2	784	50.49	23.87	6.00	136.00
	SO_2	784	16.86	19.59	2.00	133.00
	PM 10	784	104.82	73.09	0.00	461.00
	PM 2.5	784	78.50	66.74	5.00	476.00
Shanghai	CO	782	0.86	0.32	0.37	3.08
	NO_2	782	45.23	21.24	4.00	142.00
	SO_2	782	18.40	13.15	5.00	93.00
	PM 10	782	75.64	47.41	7.00	475.00
	PM 2.5	782	55.54	39.46	6.00	461.00
Shenzhen	CO	784	1.01	0.23	0.55	1.75
	NO_2	784	32.94	12.26	10.00	101.00
	SO_2	784	8.08	4.07	3.00	49.00
	PM 10	784	55.37	28.36	14.00	182.00
	PM 2.5	784	32.83	20.65	6.00	131.00
Guangzhou	CO	784	0.99	0.26	0.53	2.61
	NO_2	784	45.46	18.09	15.00	145.00
	SO_2	784	14.67	7.17	2.00	53.00
	PM 10	784	65.91	31.73	12.00	197.00
	PM 2.5	784	44.38	24.73	8.00	155.00

Table 3: Estimates of d for the case of White noise disturbances

City	Series	No regressors	An intercept	A linear trend
	CO	0.51 (0.44, 0.60)	**0.49 (0.41, 0.58)**	0.49 (0.41, 0.58)
	NO_2	0.52 (0.46, 0.60)	**0.46 (0.39, 0.56)**	0.46 (0.39, 0.56)
Beijing	SO_2	0.51 (0.46, 0.57)	**0.49 (0.44, 0.56)**	0.48 (0.43, 0.56)
	PM 10	0.49 (0.41, 0.59)	**0.47 (0.38, 0.58)**	0.47 (0.38, 0.58)
	PM 2.5	0.53 (0.44, 0.64)	**0.53 (0.43, 0.65)**	0.53 (0.43, 0.65)
	CO	0.53 (0.48, 0.59)	**0.46 (0.40, 0.54)**	0.46 (0.40, 0.54)
	NO_2	0.59 (0.53, 0.67)	**0.55 (0.48, 0.64)**	0.55 (0.48, 0.64)
Shanghai	SO_2	0.57 (0.51, 0.62)	**0.53 (0.47, 0.60)**	0.53 (0.47, 0.60)
	PM 10	0.49 (0.43, 0.56)	**0.45 (0.38, 0.53)**	0.44 (0.37, 0.53)
	PM 2.5	0.46 (0.40, 0.53)	**0.42 (0.36, 0.50)**	0.42 (0.35, 0.50)
	CO	0.72 (0.67, 0.77)	**0.59 (0.53, 0.66)**	0.59 (0.53, 0.66)
	NO_2	0.51 (0.45, 0.57)	**0.44 (0.37, 0.51)**	0.44 (0.37, 0.51)
Shenzhen	SO_2	0.63 (0.57, 0.70)	**0.61 (0.54, 0.68)**	0.61 (0.54, 0.68)
	PM 10	0.72 (0.66, 0.80)	**0.71 (0.63, 0.79)**	0.71 (0.63, 0.79)
	PM 2.5	0.73 (0.66, 0.81)	**0.71 (0.64, 0.80)**	0.71 (0.64, 0.80)
	CO	0.60 (0.55, 0.66)	**0.50 (0.45, 0.58)**	0.50 (0.45, 0.58)
	NO_2	0.64 (0.58, 0.72)	**0.61 (0.54, 0.70)**	0.62 (0.54, 0.70)
Guangzhou	SO_2	0.61 (0.55, 0.68)	**0.57 (0.50, 0.66)**	0.58 (0.51, 0.66)
	PM 10	0.63 (0.56, 0.70)	**0.60 (0.53, 0.68)**	0.61 (0.54, 0.68)
	PM 2.5	0.63 (0.58, 0.71)	**0.61 (0.54, 0.69)**	0.61 (0.55, 0.69)

Table 4: Estimates of d for the case of AR(1) disturbances

City	Series	No regressors	An intercept	A linear trend
Beijing	CO	0.24 (0.20, 0.32)	**0.20 (0.15, 0.26)**	0.20 (0.14, 0.26)
	NO_2	0.31 (0.25, 0.37)	**0.20 (0.15, 0.26)**	0.18 (0.11, 0.25)
	SO_2	0.39 (0.34, 0.44)	**0.35 (0.31, 0.40)**	0.32 (0.27, 0.38)
	PM 10	0.13 (0.06, 0.21)	**0.09 (0.04, 0.15)**	0.05 (0.00, 0.13)
	PM 2.5	0.10 (0.03, 0.18)	**0.08 (0.02, 0.14)**	0.07 (0.01, 0.14)
Shanghai	CO	0.39 (0.35, 0.44)	**0.26 (0.21, 0.32)**	0.25 (0.20, 0.32)
	NO_2	0.40 (0.35, 0.46)	**0.31 (0.26, 0.37)**	0.31 (0.25, 0.37)
	SO_2	0.47 (0.41, 0.53)	**0.39 (0.33, 0.46)**	0.37 (0.31, 0.45)
	PM 10	0.30 (0.24, 0.36)	**0.21 (0.15, 0.27)**	0.18 (0.11, 0.26)
	PM 2.5	0.30 (0.24, 0.36)	**0.21 (0.16, 0.28)**	0.19 (0.13, 0.26)
Shenzhen	CO	0.64 (0.58, 0.70)	**0.45 (0.39, 0.49)**	0.41 (0.34, 0.48)
	NO_2	0.38 (0.31, 0.44)	**0.23 (0.17, 0.30)**	0.22 (0.16, 0.29)
	SO_2	0.47 (0.41, 0.56)	**0.37 (0.27, 0.49)**	0.37 (0.26, 0.49)
	PM 10	0.45 (0.36, 0.54)	**0.35 (0.26, 0.46)**	0.35 (0.25, 0.46)
	PM 2.5	0.47 (0.39, 0.56)	**0.39 (0.32, 0.49)**	0.39 (0.31, 0.49)
Guangzhou	CO	0.50 (0.44, 0.56)	**0.33 (0.28, 0.39)**	0.32 (0.27, 0.38)
	NO_2	0.41 (0.34, 0.49)	**0.29 (0.21, 0.38)**	0.28 (0.20, 0.38)
	SO_2	0.42 (0.32, 0.53)	**0.27 (0.17, 0.38)**	0.11 (0.01, 0.37)
	PM 10	0.43 (0.35, 0.53)	**0.31 (0.22, 0.41)**	0.30 (0.20, 0.42)
	PM 2.5	0.44 (0.35, 0.54)	**0.32 (0.24, 0.42)**	0.31 (0.22, 0.43)