Australian National University

Crawford School of Public Policy

Centre for Climate Economics & Policy

Economic growth and particulate pollution concentrations in China

CCEP Working Paper 1603
Feb 2016

David I. Stern
Crawford School of Public Policy, The Australian National University

Donglan Zha
College of Economics and Management, Nanjing University of Aeronautics and Astronautics

Abstract
Though the environmental Kuznets curve (EKC) was originally developed to model the ambient concentrations of pollutants, most subsequent applications have focused on pollution emissions. Yet, it seems more likely that economic growth could eventually reduce the concentrations of local pollutants than emissions. We examine the role of income, convergence, and time related factors in explaining recent changes in PM 2.5 and PM 10 particulate pollution in 50 Chinese cities using new measures of ambient air quality that the Chinese government has published only since the beginning of 2013. We use a recently developed model that relates the rate of change of pollution to the growth of the economy and other factors as well as the traditional environmental Kuznets curve model. Pollution fell sharply from 2013 to 2014. We show that economic growth, convergence, and time effects all served to lower the level of pollution. The results also demonstrate the relationship between the two modeling approaches.

Keywords:
Air pollution; economic growth; environmental Kuznets curve; China

JEL Classification:
O44, P28, Q53, Q56

Suggested Citation:
Stern, D.I. and Zha, D. (2016), Economic growth and particulate pollution concentrations in China, CCEP Working Paper 1603, Feb 2016. Crawford School of Public Policy, The Australian National University.

Address for Correspondence:
Donglan Zha
College of Economics and Management
Nanjing University of Aeronautics and Astronautics
PO Box 150
Jiangning District
Nanjing 210016
China
Email: zdl@nuaa.edu.cn

The Crawford School of Public Policy is the Australian National University's public policy school, serving and influencing Australia, Asia and the Pacific through advanced policy research, graduate and executive education, and policy impact.

The Centre for Climate Economics & Policy is an organized research unit at the Crawford School of Public Policy, The Australian National University. The working paper series is intended to facilitate academic and policy discussion, and the views expressed in working papers are those of the authors. Contact for the Centre: Dr Frank Jotzo, frank.jotzo@anu.edu.au

Economic Growth and Particulate Pollution Concentrations in China

1. Introduction

There has been much recent concern about hazardous levels of particulate pollution in some Chinese cities (e.g. Wong, 2015), which the Chinese government has been attempting to reduce (Victor *et al.*, 2015). In this paper, we examine the role of income, convergence, and time related factors in explaining recent changes in PM 2.5 and PM 10 particulate pollution in 50 Chinese cities. We use a recently developed model that relates the rate of change of pollution to the growth of the economy and other factors, as well as the traditional environmental Kuznets curve model. We also use new measures of ambient air quality that the Chinese government has published only since the beginning of 2013. Particulate pollution fell sharply from 2013 to 2014. We show that economic growth, convergence, and time effects all served to lower the level of pollution.

The environmental Kuznets curve (EKC) has been the dominant approach among economists to modeling ambient pollution concentrations and aggregate emissions since Grossman and Krueger (1991) introduced it a quarter of a century ago. The EKC is characterized by an income turning point – the level of GDP per capita after which economic growth reduces rather than increases environmental impacts. Though the environmental Kuznets curve (EKC) was originally developed to model the ambient concentrations of pollutants, most subsequent applications have focused on pollution emissions and in particular carbon dioxide and sulfur dioxide (Carson, 2010). Recent studies using global data sets find that, in fact, income has a monotonic positive effect on the emissions of both these pollutants (Wagner, 2008; Vollebergh *et al.*, 2009; Stern, 2010; Anjum *et al.*, 2014).

Both Selden and Song (1994) and Stern *et al.* (1996) already noted that ambient concentrations of pollutants were likely to fall before emissions did. Stern (2004) suggests that this may be due to both the decline in urban population densities and the decentralization of industry that tend to accompany economic growth. Furthermore, actions through which governments can try to reduce local air pollution include moving industry outside of populated areas and building taller smokestacks. The latter reduced urban air pollution in developed countries in the 20th Century at the expense of increasing acid rain in neighboring countries and the formation of sulfate aerosols (Wigley and Raper, 1992). Additionally, pollutants with severe and obvious human health impacts such as particulates are more likely to be controlled earlier than pollutants with less obvious impacts such as carbon dioxide (Shafik, 1994). Despite this, relatively little recent research has attempted to apply the EKC to concentrations rather than emissions.

More recently, it has become popular to model the evolution of emissions using convergence approaches. Pettersson *et al.* (2013) provide a review of the literature on convergence of carbon emissions. There are three main approaches to testing for convergence: sigma convergence, which tests whether the dispersion of the variable in question declines over time using either just its variance or its full distribution (e.g. Ezcurra, 2007); stochastic convergence, which tests whether the time series for different countries cointegrate; and beta convergence, which tests whether the growth rate of a variable is negatively correlated to the initial level. We are not aware of attempts to test for convergence in pollution concentrations rather than emissions. Yet, it seems reasonable that high concentrations of pollution would encourage defensive action to reduce that pollution (Ordás Criado *et al.*'s, 2011).

Anjum *et al.* (2014) propose a model that nests both the EKC and beta convergence models. It can be seen as an extension of Ordás Criado *et al.*'s (2011) model to also include the EKC effect. The model allows us to test the contributions of economic growth, convergence, and time effects to the evolution of pollution. In this paper, we apply this model to recent data on concentrations of particulate pollution in Chinese cities. We also estimate the traditional EKC model. The results show that there is a very close relationship between the two approaches in the two period panel we have here.

The next section of the paper reviews previous research on modeling particulate pollution concentrations, with particular reference to China. The third section presents our modeling approach and the fourth our results. The fifth section presents our conclusions.

2. Previous Research

Grossman and Krueger (1991) estimated the first EKC models as part of a study of the potential environmental impacts of NAFTA. They estimated EKCs for SO_2, dark matter (fine smoke), and suspended particles (SPM) using the GEMS dataset. This dataset is a panel of ambient measurements from a number of locations in cities around the world. Each regression involved a cubic function in levels (not logarithms) of PPP (Purchasing Power Parity adjusted) per capita GDP, various site-related variables, a time trend, and a trade intensity variable. The turning points for SO_2 and dark matter were at around $4,000-5,000 while the concentration of suspended particles appeared to decline even at low income levels. However, Harbaugh *et al.* (2002) re-examined an updated version of Grossman and Krueger's data. They found that the locations of the turning points for the various pollutants, as well as even their existence, were sensitive both to variations in the data sampled and to reasonable changes in the econometric specification.

Shafik's (1994) study was particularly influential, as its results were used in the 1992 *World Development Report*. Shafik estimated EKCs for ten different indicators using three different functional forms. She found that local air pollutant concentrations conformed to the EKC hypothesis with turning points between \$3,000 and \$4,000. Selden and Song (1994) estimated EKCs for four emissions series: SO_2, NO_x, SPM, and CO. The estimated turning points were all very high compared to the two earlier studies. For the fixed effects version of their model they are (in 1990 US dollars): SO_2, \$10,391; NO_x, \$13,383; SPM, \$12,275; and CO, \$7,114. This showed that the turning points for emissions were likely to be higher than for ambient concentrations.

While there has been little recent EKC research on particulate pollution, there are a couple of recent studies for China, which are discussed below. Additionally, Keene and Deller (2015) recently published an EKC analysis of PM 2.5 for a cross-section of U.S. counties. The model includes state dummies and various control variables and they use OLS and spatial econometric estimators. They find that the peak of the EKC occurs at between US\$24,000 and US\$25,500, depending on the estimator used, which is very similar to their estimate for PM 2.5 emissions. This is not so surprising given that they use modeled concentrations that cover all counties in the country rather than the small number of urban locations covered by most concentrations EKC studies.

Van Donkelaar (2010) showed from satellite data that the highest concentrations of PM 2.5 in the World were in Eastern China. Only 24 of 350 Chinese prefectures had annual average PM 2.5 concentrations below the World Health Organization guideline of 10 $\mu g/m^3$ between 2001 and 2006 (Han *et al.*, 2014). Zhao *et al.* (2013) review developments in air pollution and policy in China between 2005 and 2010. They found that total PM emissions fell by 13% over that period due to significant efforts at pollution control particularly in the power generation, cement production, and iron and steel sectors over the 5-year period. PM 10 and PM 2.5 emissions declined by 10% and 6%, respectively. They also noted that:

> "China's air pollution challenges have been expanding from developed urban areas to nearby regions… China's rapid urbanization of relatively small cities and development policies targeting interior regions have spread economic growth to less developed areas, resulting in increased industrial production and energy consumption. Meanwhile, tightened emission controls in the most highly developed, heavily polluted urban areas has lead to relocation of major emission sources from urban to rural regions." (p. 504).

Most research on the relationship between economic growth and air pollution in China also examines emissions rather than concentrations (e.g. Poon *et al.*, 2006; Song *et al.*, 2008; He, 2009; Cole *et al.*, 2011; Lee and Oh, 2015). However, there are a few studies using concentrations data.

Brajer *et al.* (2011) investigate ambient concentrations of SO_2, NO_2, and total suspended particulates and also construct indices of total air pollution using the Nemerow approach and an alternative proposed by Khanna (2000). Their data cover the period 1990-2006 for 139 Chinese cities. They use a logarithmic EKC model with city random effects and a linear time trend with the addition of population density variable. Using the quadratic EKC model, they estimate the turning point for TSP at RMB 3,794, not controlling for population density, and at RMB 6,253, controlling for population density. However, the regression coefficient of the cube of log income in a cubic EKC model is statistically significantly greater than zero. This second turning point occurs around RMB 125k.

Hao and Yu (2016) estimate EKC models for PM2.5 concentrations and the official Air Quality Index in a cross-section of 73 Chinese cities in 2013. They find an inverted U shape curve with highly significant parameter estimates for OLS and SEM estimates, with turning points of RMB 9k to 40k and PM 2.5, respectively.

3. Models

Based on Anjum *et al.* (2014), the growth rates model of the relationship between pollution concentrations and income per capita is:

$$\hat{C}_i = \alpha_0 + \alpha_1 \hat{Y}_i + \alpha_2 \hat{Y}_i Y_{i,0} + \alpha_3 Y_{i,0} + \alpha_4 C_{i,0} + \varepsilon_i \tag{1}$$

Where the growth rate of pollution concentrations is given by $\hat{C}_i = \left(C_{i,T} - C_{i,0}\right)/T$ and of income per capita by $\hat{Y}_i = \left(Y_{i,T} - Y_{i,0}\right)/T$. C is the log of concentrations and Y is the log of GDP per capita. $T+1$ is the time dimension of the data, the initial year is normalized to 0 so that T indicates the final year, and i indexes the N cities. We deduct the sample mean from both the levels variables prior to estimation. α_0 is, therefore, an estimate of the mean of $\hat{C}_i$ for a city with zero economic growth and with the levels variables at their sample means. This is equivalent to the average change in the time effect in traditional panel data EKC models. If $\alpha_0 < 0$ then in the absence of economic growth (and when the other variables are at their mean values) there is on average a reduction in emissions over time, and *vice versa*. Similarly, α_1 is an estimate of the emissions-income elasticity at the sample mean of log income when the levels variables are at their sample means.

The third term on the RHS, $\hat{Y}_i Y_{i,0}$, is the interaction between the rate of economic growth and the initial level of log income. This term is intended to test the EKC hypothesis that there is a level of income above which economic growth is associated with a decline in concentrations, *ceteris paribus*. For the EKC hypothesis to hold, α_2 must be significantly less than zero. If we estimate (1) without demeaning Y_{i0}, then, assuming that $\tilde{\alpha}_1 > 0$ (where the tilde indicates the parameter estimate without demeaning) and $\alpha_2 < 0$, we can compute the EKC turning point using $\mu = \exp(-\tilde{\alpha}_1/\alpha_2)$. We use the delta method to compute the standard error of this turning point. If α_2 is significantly less than zero but the EKC turning point is at a very high level we can conclude that while the emissions-income elasticity is lower for countries with higher GDP per capita, it does not become negative as would be required for an EKC downturn. Of course, if $\tilde{\alpha}_1 < 0$ and $\alpha_2 > 0$ there will be an income turning point where pollution is at a minimum level instead.

The fourth and fifth terms are the initial logs of income and pollution concentrations, which are intended to test for beta-convergence. If $\alpha_4 < 0$ then there is beta-convergence in the level of concentrations. The log of income allows the time effect to vary across cities at different income levels.

We also estimate an "EKC" model where we exclude the two levels variables:

$$\hat{C}_i = \alpha_0 + \alpha_1 \hat{Y}_i + \alpha_2 \hat{Y}_i Y_{i0} + \varepsilon_i \tag{2}$$

and a simple linear model:

$$\hat{C}_i = \alpha_0 + \alpha_1 \hat{Y}_i + \varepsilon_i \tag{3}$$

We also estimate the traditional EKC model:

$$C_{i,t} = \gamma_i + \gamma_t + \beta_1 Y_{i,t} + \beta_2 Y_{i,t}^2 + e_{it} \quad (4)$$

Here all the variables are in log levels and γ_i and γ_t are city and time effects, respectively. We use the fixed effects estimator to estimate the model. We demean the log of income per capita prior to computing its square and estimating the model. The EKC turning point can be computed as $\mu = \exp(-0.5\bar{\beta}_1/\beta_2)$ where $\bar{\beta}_1$ is the parameter estimated without demeaning the variables. We also estimate the restricted linear model:

$$C_{i,t} = \gamma_i + \gamma_t + \beta_1 Y_{i,t} + e_{i,t} \quad (5)$$

When $T = 2$, as is the case for our data set, fixed effects and first differences estimators produce identical estimates (Wooldridge, 2015, p439). Therefore, in Equations (3) and (5) $\alpha_1 = \beta_1$, as the growth rates model is a model in first differences. There is also, therefore, no concern about spurious regression regarding the fixed effects estimates.

4. Data

We collected annual average PM2.5 and PM10 data in µg/m3 from the 2014 and 2015 *China Statistical Yearbooks*. This data is available for 51 key environmental protection cities, whose data are estimated according to the new Ambient Air Quality Standard (GB3095-2012) implemented on 1st January 2013. Therefore, data collected since that date are not comparable to data from previous years and, so, we only use 2013 and 2014 annual data. Similarly, Stoerk (2015) shows that misreporting of air quality data for Beijing likely ended in 2012. Population is based on the sixth China population census in 2010 (*Province Report of Population Census),* which we then project to 2013 and 2014 using the growth rates implied by the city populations in the *China City Statistic Yearbook*. The latter only included the population with registration (*hukou*) in those cities and exclude migrant workers. Gibson and Li (2015) note that most studies of the Chinese economy use *hukou* registrations to measure the population. However, this ignores migrant workers and so can distort estimated GDP per capital severely. Our combination of census numbers and *hukou* population growth should largely alleviate this problem.

We dropped data for Hefei (Capital of Anhui province) because of anomalous population data. In 2011, the neighboring city of Chaohu was dissolved and parts of its territory merged into Hefei and other cities (Zhang, 2011) resulting in a steep jump in Hefei's population.

The remaining fifty cities are:

Beijing, Changchun, Changsha, Chengdu, Chongqing, Dongguan, Foshan, Fuzhou, Guangzhou, Guiyang, Haikou, Hangzhou, Harbin, Hohhot, Huizhou, Huzhou, Jiangmen, Jiaxing, Jinan, Jinhua, Kunming, Lanzhou, Lhasa, Lishui, Nanchang, Nanjing, Nanning, Ningbo, Qingdao, Quzhou, Shanghai, Shaoxing, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Taizhou, Tianjin, Urumqi, Wenzhou, Wuhan, Xi'an, Xiamen, Xining, Yinchuan, Zhaoqing, Zhengzhou, Zhongshan, Zhoushan, and Zhuhai.

Total GDP in 2013 RMB is from the *China City Statistic Yearbook*. We divided this data by our population estimate to obtain GDP per capita.

Table 1 presents summary statistics for our variables. We present the statistics for natural levels of the variables, as demeaned logs are not very intuitive. Income per capita shows a more than threefold range across the 50 Chinese cities from the poorest city (Nanning) to the richest (Beijing). Per capita income rose in all cities from 2013 to 2014 at an average rate of 6.9%, but here too there is a wide range of growth rates from 1.5% in Shenzhen to 9.9% in Wuhan. Pollution levels vary much more widely with a six-fold difference between the least polluted cities (Lhasa in 2013 for PM 2.5 and Haikou (Hainan province) in 2014 for PM 2.5 and for both years for PM 10) to the most polluted city – Shijiazhuang. There was a large average decline in pollution from 2013 to 2014 of 15.5% for PM 2.5 and 14.3% for PM 10. Again, there was much variation across cities. The largest declines were in Xian and Shijiazhuang for PM 2.5 and PM 10, respectively, and the largest increases in Zhaoqing (Guangdong province, PM 2.5) and Beijing (PM 10).

Figures 1 and 2 present the data in levels. The graphs use the 2013-14 mean for each variable. The patterns for the two sizes of particles are similar with a decreasing variance of pollution levels with increasing income. Note that the data in the graph are the city means that are first deducted from the data to estimate the fixed effects model and are implicitly eliminated in the growth rates model. Figures 3 and 4 present the data in growth rates form. There is some indication of a negative correlation between the growth rates of pollution and income. The correlation for PM 2.5 is -0.17, while for PM 10 it is only -0.04.

5. Results

Table 2 presents the econometric results for the growth rates models. There is a strong negative and highly significant time effect of from 10 to 15%. It is impossible to know how much of this effect represents permanent improvements and how much year-to-year fluctuations, given our two year sample. Renewed alarm about pollution levels in 2015 (e.g. Wong, 2015) suggests that it may not all be permanent.

The effect of growth at the sample mean is not statistically significant in any of the specifications but care is needed in interpreting these results. For PM 2.5, none of the growth related parameters are statistically significant, but there is a highly significant turning point for the full specification at RMB 86k. The regression parameters are not significant because mean income per capita is at RMB 76k. However, the EKC is U-shaped rather than an inverted U. But, when we remove the levels variables, the turning point is at RMB 418k, though this is not precisely estimated.

For PM 10 there is a turning point at RMB 58k for the full specification, but it is not precisely estimated. Note that the parameters of both growth variables are positive (though not statistically significant) yet the EKC has a U-shape. This is because the turning point is below mean income per capita and so the effect of growth is positive at the mean income level. Removing the two levels variables results in a U shape EKC with a highly significant turning point at RMB 82k and a significant coefficient for the interaction term. In conclusion, there is some evidence of a U-shape EKC for both these variables, but while this is only revealed for PM 2.5 when the convergence terms are added, this apparent effect disappears for PM 10 when the convergence terms are added.

The level of concentrations has a highly significant negative effect on both pollutants. Given that we only have two years of data this could simply represent regression to the mean in cities where pollution was particularly high or low in 2013 rather than an actual economic process.

Table 3 presents the econometric results for the traditional EKC models. As expected, results for the linear specification are identical to those for the growth rates model. But the quadratic specification also is very similar to the growth rates specification with $\beta_1 \approx \alpha_1$ and $\beta_2 \approx 0.5\alpha_2$. The turning points are also only a little higher than the corresponding turning points for the growth rates models.

6. Conclusions

The evidence presented in this article shows that there were large negative time effects in particulate pollution concentrations between 2013 and 2014 for a sample of 50 large Chinese cities. There is also clear evidence of convergence with concentrations falling faster in more highly polluted cities. Given only two years of data it is hard to know how permanent these changes are. The effect of economic growth is much more ambiguous. When controlling for initial concentrations, there is some evidence of a positive effect of growth on concentrations at high income levels and a negative effect at low income levels though this is completely statistically insignificant for PM 10 unless the levels variables are excluded from the equation. What is clear, is that this behavior is very different from emissions of sulfur or greenhouse gases where typically a strong positive effect of economic growth is found at the sample mean income (Anjum *et al.*, 2014; Sanchez and Stern, 2015). The global sample mean income is close to that in China.

The most directly comparable previous study is Hao and Lu (2016), who found an inverted U shape EKC for 2013 PM 2.5 concentrations in 73 Chinese cities. Using our data for 2013 alone, we also obtain an inverted U-shape EKC. But none of the regression coefficients are statistically significant and the turning point is at RMB 117k. Hao and Lu used data provided by a private company called Fresh Ideas Studio, while we use the official statistics. This difference in source and the number of cities covered might explain the differences between our estimates. But it also shows that a single year of data is not very informative. Obviously, we need more years of good quality Chinese data to better understand the factors driving pollution concentrations in the country. The results suggest that it is worthwhile to investigate further pollution concentration variables around the world using recent data and methods as the results may be quite different than those for pollution emissions.

References

Anjum, Z., Burke, P. J., Gerlagh, R., & Stern, D. I. (2014). Modeling the emissions-income relationship using long-run growth rates. *CCEP Working Papers* 1403.

Brajer, V., Mead, R. W. Xiao, F. (2011) Searching for an Environmental Kuznets Curve in China's air pollution, *China Economic Review* 22, 383–397.

Carson, R. T. (2010). The environmental Kuznets curve: Seeking empirical regularity and theoretical structure. *Review of Environmental Economics and Policy*, 4(1), 3–23.

Cole, M. A., Elliott, R. J. R., & Zhang, J. (2011) Growth, foreign direct investment, and the environment: evidence from Chinese cities, *Journal of Regional Science* 51(1), 121–138.

Ezcurra, R. (2007). Is there cross-country convergence in carbon dioxide emissions? *Energy Policy*, 35, 1363-1372.

Gibson, J. & Li, C. (2015) The erroneous use of China's population and *per capita* data: a structured review and critical test, *University Of Waikato Working Paper in Economics* 14/15.

Grossman, G. M. & Krueger, A. B. (1991). Environmental impacts of a North American Free Trade Agreement. *NBER Working Papers*, 3914.

Han, L., Zhou, W, Li, W., Li, L. (2014) Impact of urbanization level on urban air quality: A case of fine particles (PM 2.5) in Chinese cities, *Environmental Pollution* 194, 163-170.

Hao, Y. & Liu, Y.-M. (2016) The influential factors of urban PM 2.5 concentrations in China: a spatial econometric analysis, *Journal of Cleaner Production* 112, 1443-1453.

Harbaugh, W., Levinson, A., & Wilson, D. (2002). Re-examining the empirical evidence for an environmental Kuznets curve. *Review of Economics and Statistics*, 84(3), 541–551.

He, J. (2009) China's industrial SO2 emissions and its economic determinants: EKC's reduced vs. structural model and the role of international trade, *Environment and Development Economics* 14(2), 227–262.

Keene, A. & Deller, S. C. (2015) Evidence of the environmental Kuznets' curve among US counties and the impact of social capital, *International Regional Science Review* 38(4), 358-387.

Khanna, N. (2000) Measuring environmental quality: An index of pollution, *Ecological Economics* 35, 191–202.

Lee, H. & Oh, D. (2015) Economic growth and the environment in China: Empirical evidence using prefecture level data, *China Economic Review* 36, 73-85.

Ordás Criado, C., Valente, S., & Stengos, T., 2011. Growth and pollution convergence: Theory and evidence. *Journal of Environmental Economics and Management*, 62, 199-214.

Pettersson, F., Maddison, D., Acar, S., & Söderholm, P. (2013). Convergence of carbon dioxide emissions: A review of the literature. *International Review of Environmental and Resource Economics*, 7, 141–178.

Poon, J. P. H., Casas, I., & He, C. (2006) The impact of energy, transport, and trade on air pollution in China, *Eurasian Geography and Economics* 47(5), 568-584.

Sanchez, L. F. & Stern, D. I. (in press) Drivers of industrial and non-industrial greenhouse gas emissions. *Ecological Economics*.

Selden, T. M. & Song, D. (1994). Environmental quality and development: Is there a Kuznets curve for air pollution? *Journal of Environmental Economics and Environmental Management*, 27, 147–162.

Shafik, N. (1994). Economic development and environmental quality: an econometric analysis. *Oxford Economic Papers*, 46, 757–773.

Song, T., Zheng, T., & Tong, L. (2008) An empirical test of the environmental Kuznets curve in China: A panel cointegration approach, *China Economic Review* 19, 381–392.

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World Development*, 32(8), 1419–1439.

Stern, D. I. (2010). Between estimates of the emissions-income elasticity. *Ecological Economics*, 69, 2173–2182.

Stern, D. I., Common, M. S., and Barbier, E. B. (1996). Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development. *World Development*, 24, 1151–1160.

Stoerk, T. (2015). Statistical corruption in Beijing's air quality data has likely ended in 2012, *Grantham Research Institute on Climate Change and the Environment Working Paper* 194.

van Donkelaar, A., Martin, R. V., Brauer, M., Kahn, R., Levy, R., Verduzco, C., and Villeneuve, P. J. (2010) Global estimates of ambient fine particulate matter concentrations from satellite-based aerosol optical depth: development and application, *Environmental Health Perspectives* 118, 847–855.

Victor, D. G., Zaelke, D., & Ramanathan, V. (2015) Soot and short-lived pollutants provide political opportunity, *Nature Climate Change* 5, 796–798.

Vollebergh, H. R. J., Melenberg, B., & Dijkgraaf, E. (2009). Identifying reduced-form relations with panel data: The case of pollution and income. *Journal of Environmental Economics and Management*, 58, 27–42.

Wagner, M. (2008). The carbon Kuznets curve: A cloudy picture emitted by bad econometrics. *Resource and Energy Economics*, 30, 388–408.

Wigley, T. M. L. & Raper, S. C. B. (1992). Implications for climate and sea level of revised IPCC emissions scenarios, *Nature* 357, 293-300.

Wong, E. (2015) Beijing issues red alert over air pollution for the first time, *New York Times* 7 December 2015.

Wooldridge, J. (2015) *Introductory Econometrics: A Modern Approach*, 6th Edition, Cengage Learning.

Zhang, Y. (2011) Three-way split to wipe Anhui city off the map. *China Daily* 22 August.

Zhao, Y., Zhang, J. and Nielsen, C. P. (2013). The effects of recent control policies on trends in emissions of anthropogenic atmospheric pollutants and CO_2 in China. *Atmospheric Chemistry and Physics*, 13, 487–508.

Table 1: Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum
		2013 Levels		
GDP per Capita	70,747	24,439	41,095	142,580
PM 2.5	65.86	24.45	26.00	154.00
PM 10	108.38	46.45	47.00	305.00
		2014 Levels		
GDP per Capita	75,765	26,016	44,237	150,688
PM 2.5	56.02	19.32	22.30	118.43
PM 10	92.82	34.82	40.27	206.71
		Growth Rates		
GDP per Capita	6.9%	1.6%	1.5%	9.9%
PM 2.5	-15.5%	7.5%	-33.2%	0.6%
PM 10	-14.3%	9.5%	-38.9%	7.7%

Table 2: Growth Rates Regression Results

	PM 2.5			PM 10		
	Eq (3)	Eq (2)	Eq (1)	Eq (3)	Eq (2)	Eq (1)
Constant	-0.1003** (0.0409)	-0.0987** (0.0417)	-0.1167*** (0.0407)	-0.1274** (0.0520)	-0.1218*** (0.0455)	-0.1486*** (0.0431)
$\dot{Y}_i$	-0.7981 (0.5965)	-0.8216 (0.6083)	-0.5571 (0.6087)	-0.2300 (0.7428)	-0.3089 (0.6669)	0.0795 (0.6497)
$Y_{i0}\dot{Y}_i$		0.4486 (0.4219)	2.2625 (1.7230)		1.5073*** (0.5463)	0.6107 (1.5194)
Y_{i0}			-0.1159 (0.1114)			0.0654 (0.1058)
C_{i0}			-0.0696*** (0.0261)			-0.0942*** (0.0308)
EKC income per capita turning point (RMB)	n.a.	417,633 (780,279)	85,569*** (22,795)	n.a.	82,109** (35,409)	58,734 (72,151)

Notes: Figures in parentheses are heteroskedasticity robust standard errors. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%.

Table 3: Environmental Kuznets Curve Regression Results

	PM 2.5		PM 10	
	Eq (5)	Eq (4)	Eq (5)	Eq (4)
Y_{it}	-0.7981 (0.5965)	-0.8343 (0.6129)	-0.2300 (0.7428)	-0.3529 (0.6694)
Y_{it}^2		0.2220 (0.2107)		0.7538*** (0.2726)
EKC income per capita turning point	n.a.	453,454 (861,463)	n.a.	87,493*** (37,677)

Notes: Figures in parentheses are robust clustered standard errors. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%.

Figure 1. Levels of PM 2.5 and GDP per Capita

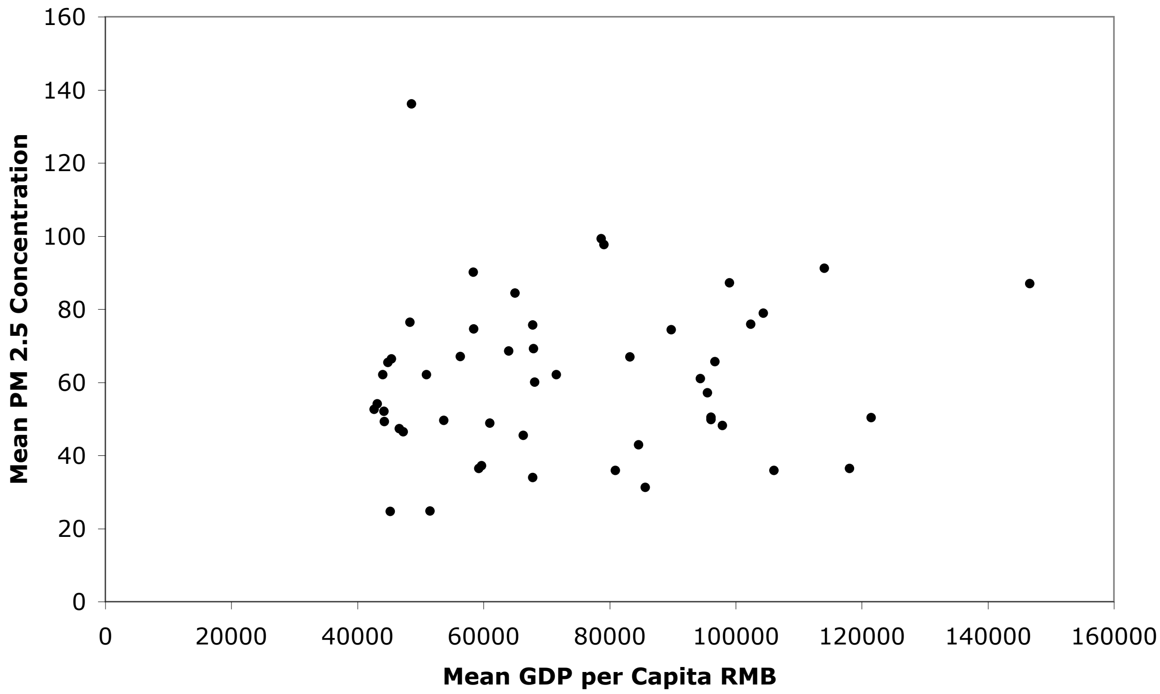

Figure 2. Levels of PM 10 and GDP per Capita

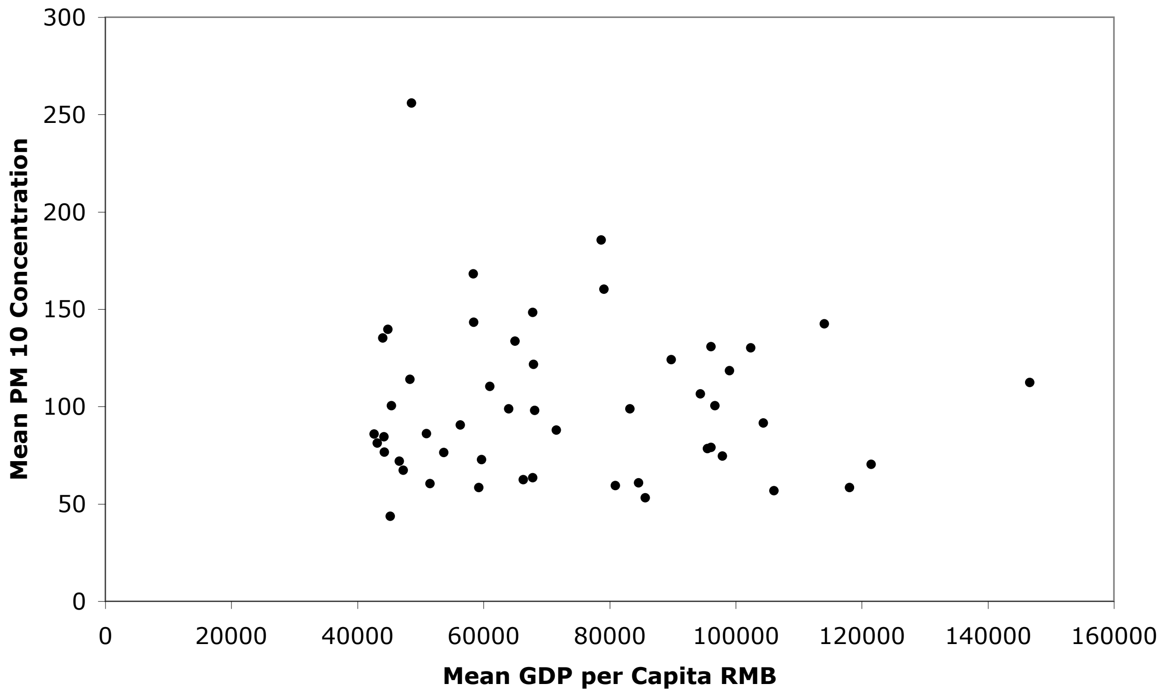

Figure 3. Growth Rates of PM2.5 and GDP per Capita

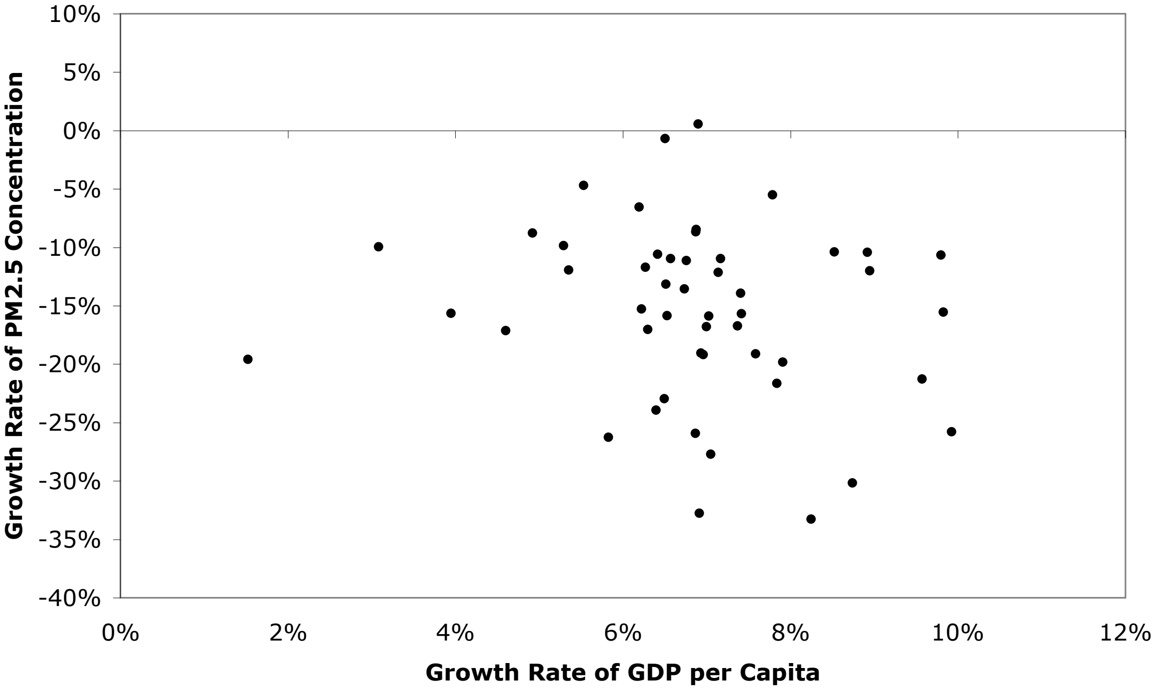

Figure 4. Growth Rates of PM 10 and GDP per Capita