Quantifying the impacts of socio-economic factors on air quality in Chinese cities from 2000 to 2009

Juanjuan Zhao^{a,b,*}, Shengbin Chen^c, Hua Wang^d, Yin Ren^{a,b}, Ke Du^e, Weihua Xu^f, Hua Zheng^f, Bo Jiang^f

^a Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, 1799 Jimei Road, Jimei District, Xiamen 361021, China

^b Xiamen Key Lab of Urban Metabolism, 1799 Jimei Road, Jimei District, Xiamen 361021, China

^c Nanjing Institute of Environmental Sciences, Ministry of Environmental Protection, Nanjing 210042, China

^d Institute of Forestry and Pomology, Beijing Academy of Agriculture and Forestry Sciences, Beijing 100093, China

^e Institute of Urban Environment, Chinese Academy of Sciences, Xiamen, China

^f State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China

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ABSTRACT

Socio-economic factors have significant influences on air quality and are commonly used to guide environmental planning and management. Based on data from 85 long-term daily monitoring cities in China, air quality as evaluated by AOFDAQ-A (Annual Occurrence Frequency of Daily Air Quality above Level III), was correlated to socio-economic variable groups of urbanization, pollution and environmental treatment by variation partitioning and hierarchical partitioning methods. We found: (1) the three groups explained 43.5% of the variance in AOFDAQ-A; (2) the contribution of “environmental investment” to AOFDAQ-A shown a time lag effect; (3) “population in mining sector” and “coverage of green space in built-up area” were respectively the most significant negative and positive explanatory socio-economic variables; (4) using eight largest contributing individual factors, a linear model to predict variance in AOFDAQ-A was constructed. Results from our study provide a valuable reference for the management and control of air quality in Chinese cities.

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1. Introduction

Urban areas are hot spots that drive environmental change (Grimm et al., 2008). The unprecedented rate of urban growth over the past century has had an enormous global impact (Brown, 2001). Although cities only cover 2.8% of the Earth's terrestrial surface, they are the major consumers of natural resources, the major producers of pollution waste, and the focus of most other human activities, many governments realize that much of the sustainability debate has an urban focus (Breheny, 1992; Marquez and Smith, 1999).

As cities are wholly created by humans (Whitney and Adams, 1980; Hope et al., 2003), the ecology and environment in and around cities reflects social, economic, and cultural influences (Liu, 2001). For example, income and education are robust determinants of household air pollution (Papineau et al., 2009), urban population density can influence total passenger vehicle emissions (Marshall et al., 2005), and economic development has positive contribution to environmental quality (Xepapadeas and Amri, 1998).

However, other reports found that when GDP increases, the larger scale of production leads directly to more pollution and more environmental damage (Zugravu et al., 2008). After all, according to Ewing et al. (2007), compact development could achieve a reduction of greenhouse gas emissions by up to 10% by 2050. Moreover, additional reductions may result from employing other strategies such as transit investment, fuel pricing, and parking (Bandeira et al., 2011).

In light of these significant influences of socio-economic factors, cities should be designed and managed to reduce environmental degradation (Marquez and Smith, 1999). At least 24% of greenhouse gas emissions sources are amenable via more enlightened urban planning and design principles and programs, increasing to 54% if transport, housing and commercial buildings are included (Marquez and Smith, 1999). Information is then needed on the technological and planning options available and how much these can help to reduce emissions and at what cost (Mediavilla-Sahagun and ApSimon, 2006). By determining their power to explain the variance in air quality, socio-economic indices could be more practically and expediently used to connect air quality control with urban planning and policy making. Such an approach should be transparent to both the responsible authorities and to the affected public (Mediavilla-Sahagun and ApSimon, 2006). Yet relative

* Corresponding author.

E-mail addresses: jjzhao@iue.ac.cn, zhao.juanjuan.cn@gmail.com (J. Zhao).

studies on the contribution of policy and planning to explain the variance in air quality have only been sporadically reported (Bandeira et al., 2011).

Air pollution in Chinese cities has become one of the top environmental concerns. As a typical developing country, China has an urban population of 621.86 million, accounting for 46.56% of the total population (Editorial Board of China Statistical Yearbook, 2010). In the last two decades, knowledge on air pollution has improved considerably as funding for environmental research has increased (Florig et al., 2002; Chan and Yao, 2008). Air quality monitoring systems have been installed in over 200 cities, some of which began monitoring in the year 2000, and the number of monitored cities continues to increase. The daily reports of air quality in the monitored cities provide important basic data for air quality research.

Socio-economic factors are always important in macro-control of national environmental pollution, and are used to guide environmental treatments. In this research, we hypothesized that air quality in cities is affected by the interrelated socio-economic factors that characterize the human disturbance. The air quality of 85 cities covering all provinces in mainland China with the exception of Tibet were assessed with respect to 21 environmental factors divided into three groups i.e. urbanization, pollution and environmental treatment. Specifically, we posted the following research questions: (1) Do the methods of partitioning analysis applicable to distinguish the relative importance of socio-economic variable groups to air quality? (2) To what extents the contributions of pollution, urbanization and environmental treatment account for variations in urban tree transpiration? (3) Which socio-economic variables are the most important predictors of urban air quality? The results from this research provide insights into the causal socio-economic variables of urban air quality, and provide valuable references for the management and control of air quality in Chinese cities.

2. Materials and methods

2.1. Study sites

Air quality samples were collected at 85 long-term daily monitoring sites (see Appendix A), covering all provinces in mainland China with the exception of Tibet, for which socio-economic data were unavailable. Most of the monitoring sites were in relatively developed cities in each province. The location and monitoring effort for each site is shown in the Appendix A. A map showing the distribution of these sites in China can be seen in the Ministry of Environmental Protection of the People's Republic of China website (MEPPRC, <http://www.zhb.gov.cn>; Chinese National Environmental Monitoring Centre, 2010). As monitoring at different sites began at different times, the monitoring periods also varies between sample sites (see Appendix A).

2.2. Data

2.2.1. Air quality

To quantify air quality, an air pollution index (API; National Bureau of Statistics of China, 2008) has been in use at the monitoring sites since 1997. Daily average API values of all the monitoring cities are reported at the official website (<http://www.zhb.gov.cn>).

Based on the API, ambient air quality of monitored cities are classified into five levels and also reported on the MEPPRC website (Table 1). These reports provide overviews of air quality across mainland China.

API reporting requires monitored daily average air quality data to be converted into integer values (Jiang et al., 2004). API is measured as the maximum pollution sub-index of pollutants by the following formula (National Bureau of Statistics of China, 2008):

$$API = \text{Max}\{I_1, I_2, \dots, I_n\}$$

where I_x is the air pollution index for pollutant X, and n is the number of pollutants.

For pollutant X, I_x is calculated by the following formula:

$$I_x = \frac{(C_x - C_{xj})}{C_{xj+1} - C_{xj}} (I_{xj+1} - I_{xj}) + I_{xj}$$

Where $C_{xj} < C_x \leq C_{xj+1}$, C_x is the concentration of pollutant X (mg/m^3), C_{xj} is the threshold concentration of pollutant X for level j that is $\leq C_{xj}$, C_{xj+1} is the threshold concentration for level $j+1$ that is $\geq C_{xj+1}$, I_{xj} is the index of pollutant X for level j , and I_{xj+1} is the index for level $j+1$.

For the indices for different levels of pollutants, see the published technical manual for urban ambient air quality daily report and forecast in China (National Bureau of Statistics of China, 2008).

The pollutants in the daily report include daily average concentrations of SO_2 , NO_2 , PM_{10} and CO, and eight hour (9:00–17:00) averaged concentration of O_3 (National Bureau of Statistics of China, 2008). Since the API is simply the maximum value of the normalized concentrations at a given site, the various pollutants are ascribed equal importance in describing the overall air quality (Liu and Chan, 2002). Technical details concerning the monitoring sites, monitoring methods and statistical methods have been described in Automatic Monitoring Technical Specifications of Ambient Air Quality (HJ/T 193–2005; National Bureau of Statistics of China, 2005a), and Manual Monitoring Technical Specifications of Ambient Air Quality (HJ/T 194–2005; National Bureau of Statistics of China, 2005b).

The Annual Occurrence Frequency of Daily Air Quality above Level III (including air quality level I and II, abbreviated as AOFDAQ-A, and not poor air quality levels III, IV and V), which means better air quality when outdoor activity is not affected, is widely used in China for governmental planning and scientific research. In this paper we took daily air quality observation records from 2000 to 2009 (Chinese National Environmental Monitoring Centre, 2010), and calculated the AOFDAQ-A for each city in each year by dividing the total number of days with daily air quality better than level III by the number of days with valid observations.

2.2.2. Socio-economic variables

Socio-economic predictor variables data was collected from the Statistics Yearbook of Cities in China (Urban Socio Economic Survey Division of National Bureau of Statistics of China, 2001–2010). All possible socio-economic predictor factors were tested using linear regression to select those with a significant effect on air quality. According to the results, significant variables were classified into three groups, which are urbanization, pollution and environmental treatment (Table 2). We identified urbanization variables as a separate group because they were related to both pollution and environmental treatment. Where variables were recorded for different periods of time, data were analyzed during separate runs.

2.2.3. Linear regression

Linear regressions were conducted for each explanatory variable to select the significant variables. For each of the linear regressions, an approximately normal distribution of the residuals was proved by QQ-plot of model residuals and boxplot of residuals, and Levene's test was used to test for homogeneity of variances for the residuals.

Using SPSS 16.0, a multi-variables linear regression was conducted with the eight most significant and least collinear variables to model the value of AOFDAQ-A. The error term had a normal distribution with a mean of <0.001 .

Table 1

Classification criteria of air quality (translated from National Bureau of Statistics of China, 2008).

Air quality index (API)	Air quality level	Air quality condition	At risk population	Health implications
0–50	I	Excellent	Usual outdoor activities	None
51–100	II	Good		
101–200	III	Lightly polluted	Mild aggravation of symptoms among susceptible persons. Generally healthy individuals may also notice some discomfort.	People with breathing or heart problems should restrict physical exercises and outdoor activities.
201–300	IV	Moderately polluted	Moderate aggravation of symptoms and decreased tolerance in persons with heart or lung disease. More widespread symptoms of transient irritation in the healthy population.	Elders and people with existing heart or respiratory illnesses should remain indoors and avoid exercise.
>300	V	Intensively polluted	Healthy people may experience decreased exercise tolerance and adverse symptoms that affect normal activity, in addition to early onset of certain diseases.	Elders and the sick should remain indoors and avoid exercise. Healthy individuals should avoid outdoor activities.

Table 2

Statistical inferences of variation partitioning on explanatory variables showing their effects on air quality.

Variable groups	Variables	Adjusted R square	
		Linear	Quadratic
Urbanization variables	Service industry as percent of GDP (SIP)	0.0360***	0.0359**
	Rural population (RP)	0.0562**	0.0959**
	Built-up area (BA)	0.0423**	0.0424**
	Land area for urban construction (LAU)	0.0226**	0.0226**
	Urban population density (UPD)	0.0257**	0.0256**
Pollution variables	Population in building industry sector (PBI)	0.0981**	0.0980**
	Population in real estate sector (PRE)	0.0149**	0.0150**
	Population in transport, storage and post sectors (PTS)	0.0767**	0.0779**
	Population in mining sector (PMiS)	0.1053**	0.0941**
	Population in manufacturing sector (PMaS)	0.0373**	NS ^b
	Residential consumption of coal gas (RCC)	0.1132**	0.1132**
	Total supply of coal gas (TSC)	0.1282**	0.1281**
	Population in the sector for production and supply of electricity, gas and water (PSP)	0.1525**	0.1325**
	Total investment in environmental pollution control as percent of GDP (TIE)	0.0110 ^c	NS
Environmental treatment variables	Area of green space in parks (AGS)	0.0122***	0.0122**
	Coverage of green space in built-up area (CGS)	0.1316**	0.1147**
	Ratio of industrial solid wastes utilized (RISw)	0.0767**	0.0772**
	Ratio of industrial waste water meeting discharge standards (RIW)	NS	0.0062*
	Ratio of industrial SO ₂ removed (RISr)	NS	0.0673**
	Treatment rate of urban consumption waste water (TRU)	0.0071*	0.0042**
	Treatment rate of consumption wastes (TRC)	0.0364**	0.0370**

a,c *** and ** indicate inferences are significant at $p < 0.01$ and $p < 0.05$ respectively.b Symbols "NS" denotes no effects; for each of the significant variables, the p -value of intercept and slope are significant at $p < 0.05$.

2.3. Variation partitioning for variable groups

Variation partitioning was used to decompose the variation in air quality, following the methods described by Anderson and Gribble (1998), Heikkinen et al. (2004, 2005), and Wang et al. (2011). This partitions the variance of AOFDAQ-A into eight fractions, namely the individual effects of urbanization, pollution, and environmental treatment, respectively; joint effects of urbanization and pollution, urbanization and environmental treatment, and pollution and environmental treatment respectively; joint effects of the three explanatory variable groups; and finally unexplained variance. To improve the comparability and the linearity of relationships between predictor variables and air quality, the socio-economic data was log-transformed.

The first step was to perform a series of linear regression for all socio-economic variables, using an R statistical package ('hier.part' package version 0.5-1, Walsh and Mac-Nally, 2003). Explanatory variables that did not contribute significantly to the variance of AOFDAQ-A at $p > 0.05$ (Borcard et al., 1992; Wang et al., 2011) were excluded. Quadratic terms of predictors were also analyzed in this procedure to take potential curvilinear relationships into account (Heikkinen et al., 2004; Wang et al., 2011). Only significant predictor variables identified in this process were included in the subsequent analyses. The other three steps to calculate the value of the eight fractions followed Wang et al. (2011).

2.4. Hierarchical partitioning for individual variables

Hierarchical partitioning aims at generating a detailed basis for inferring causality in multivariate regression settings (Watson and Peterson, 1999). To identify the contribution of individual variables that significantly affected air quality, hierarchical partitioning was conducted using R statistical package (Walsh and Mac-Nally, 2003). The functions in this package produce a minor rounding error for analyses with more than nine independent variables (Walsh and Mac-Nally, 2003), so the eight most significant and least collinear variables were selected to perform hierarchical partitioning. The partitioning was conducted using linear regression with R^2 as the goodness-of-fit measure.

Hierarchical partitioning depends on the existence of monotonic relationships between the response and the predictor variables (Heikkinen et al., 2004). Hence, for those variables which were only significant in quadratic terms, the quadratic terms were entered into the partitioning to improve the linearity of relationships between air quality and socio-economic variables (Wang et al., 2011).

In addition, following Mac-Nally (2002), statistical significances of the independent contributions of variables were tested by a randomization routine, which yielded Z-scores for the generated distribution of randomized independent contributions, and a measure of statistical significance (*) based on an upper 0.95 confidence limit (Heikkinen et al., 2005).

As a result, hierarchical partitioning provides, for each explanatory variable separately, an estimate of the independent and joint contribution with all other variables (Heikkinen et al., 2005; Chevan and Sutherland, 1991; Mac-Nally, 2000; Quinn and Keough, 2002).

3. Results

3.1. Air quality and annual variation trend

For most monitoring sites, the air quality in Chinese cities appeared to improve during the ten year period (Figs. 1 and 2). During the period 2000–2002, AOFDAQ-A below 60% occurred in 19.1%–27.7% of cities, dropping to 8.5% and 7.1% of cities in 2003 and 2004, then to 1.2% of cities in 2005–2006, and finally disappearing in the period 2007–2009 (Fig. 1). On the contrary, AOFDAQ-A above 80% exhibited an upwards trend, increasing from 46.8%–59.5% of cities in the first three years, to 63.8%–77.9% of cities in the following four years, and to 83.7%–95.3% of cities in the last three years (Fig. 1).

The highest AOFDAQ-A appeared in Zhuhai, Zhanjiang, Haikou, Guilin and Beihai, with 100% occurrence in nine or ten years. Some other cities had 95% occurrence of daily air quality above level III, including Kunming, Nanning, Xiamen, Shantou, Shenzhen, Wenzhou, and Yantai. Overall, the AOFDAQ-A for most cities during most years was higher than 80%, with the exceptions being Beijing, Lanzhou and Urumqi. On the whole, air quality of cities in the south of China was much better than in northern cities.

Fig. 1. Overview of air quality in the monitoring cities from 2000 to 2009. In 2000, 42 cities were monitored; from 2001 to 2003, 47 cities were monitored; from 2004 to 2005, 84 cities were monitored; from 2006 to 2009, 86 cities were monitored.

Fig. 2. Variation trend of air quality in the monitoring cities from 2000 to 2009. A boxplot is a graphical summary of a distribution. The box itself contains the middle 50% of the data. The upper edge (hinge) of the box indicates the 75th percentile of the data set, and the lower hinge indicates the 25th percentile. The line in the box indicates the median value of the data. The error bars represent the 5th and 95th percentile values. The points outside the ends of the whiskers are outliers or suspected outliers.

3.2. The relationship between air quality and socio-economic variables

By linear regression, 21 significant variables were identified from 72 possible explanatory variables, and divided into three groups according to their influence on air quality (Table 2). All three variable groups were found to contribute significantly to the variance of AOFAQ-A. Five variables were included in the urbanization group, and there were eight variables in both the pollution group and the environmental treatment group. Most of the variables were significant contributors both in linear and quadratic terms. When both linear and quadratic terms were significant, the linear terms were used in subsequent analyses. The urbanization variables and the pollution variables were negatively related to AOFAQ-A, while most of the environmental treatment variables had positive effects on AOFAQ-A, with the exception of “area of green space in parks”.

3.3. Relative effect of urbanization, pollution and environmental treatment

When the variance of AOFAQ-A was decomposed, the pollution group had the primary influence on air quality, with an independent contribution of 16.6%. The environmental treatment group and the urbanization group, respectively contributed 4.5% and 1.7% to the variance. The independent and joint contributions of the three groups accounted for 43.5% variance of AOFAQ-A.

Joint effects were also considerable. The largest joint effect was contributed by the three groups combined, which accounted for 9.4% of the variance (Table 3). The joint effect of the pollution and environmental treatment groups was also relatively large (6.8%). The joint effect of the urbanization and pollution groups, and joint

effect of the urbanization and environmental treatment groups, however were relatively minor, at 3.2% and 1.3% respectively.

3.4. Relative effects of individual variables

After linear regression for all individual socio-economic variables, the eight most significant variables were selected to perform a hierarchical partitioning. Among the eight most significant variables, “population in mining sector” exhibited the highest independent contribution to the variance of AOFAQ-A, followed by “total supply of coal gas” and “ratio of industrial SO₂ removed”, respectively contributing 8.0%, 6.9% and 6.0% (Fig. 3). The largest joint contribution appeared in “population in building industry sector”, “total supply of coal gas” and “coverage of green space in built-up area”, respectively 6.2%, 6.1% and 6.1% (Fig. 3).

Only three of the eight variables made a positive contribution to the variance of AOFAQ-A. The variance explained by “coverage of green space in built-up area” was the highest, followed by “ratio of industrial solid wastes utilized” (7.5%) and “ratio of industrial SO₂ removed” (6.9%).

3.5. Multi-linear regression for a model of AOFAQ-A

By linear regression, a model was constructed using the eight most significant variables as follows:

$$y = 58.671 + 5.908b_1 + 20.103b_2 + 6.276b_3 + 0.002b_4 - 2.529b_5 - 7.505b_6 - 4.256b_7 - 2.505b_8$$

where y is AOFAQ-A, b_{1-8} are the variables shown in Table 4.

According to the results of the linear regression, all coefficients were significant and the variables were indicated to make significant contributions to the model. As a whole, modeling of AOFAQ-A was desirable. The R value of 0.634 indicated a strong relationship between the variables and AOFAQ-A, and the squared R value was 0.402, meaning that nearly half the variation in AOFAQ-A was explained by the model. The VIF (variance inflation factor) values were mostly smaller than 2, so the multi-collinearity was low and the standard error of the regression coefficients would not be significantly inflated (Table 4).

4. Discussion

Air quality in cities generally deteriorates as population, traffic, industrialization and energy use increase (Mayer, 1999). However, only limited studies have been conducted to investigate the complex relationship between urban air quality and socio-economic factors. In this paper, our study yielded contrasting inferences about the relative importance of socio-economic variables to influence air quality. Some of the results provided basic information for the control and management of urban air quality in China.

The pollution group, with an independent contribution of 16.6%, accounted for the largest proportion of variance in air quality among the three groups. It is notable that although the populations of pollution-related industrial sectors are rarely used to represent pollution intensity, six of the eight significant variables in the pollution group were related populations. Since the size of the industrial sectors are likely to be correlated to respective population

Table 3
Relative effects of variable groups on air quality.

	a (U ^a)	b (P ^b)	c (E ^c)	d (U × E)	e (U × ^d E)	f (P × E)	g (U × P × E)	h (Unaccounted)
Relative effects	1.7%	16.6%	4.5%	3.2%	1.3%	6.8%	9.4%	56.5%

^a “U” denotes urbanization group.

^b “P” denotes pollution group.

^c “E” denotes environmental treatment group.

^d “×” denotes joint effect of relative groups.

Fig. 3. Contributions to the variance of AOFDAQ-A by the eight most significant variables in which “*” denotes the effect due to this variable is significant at $p < 0.05$. All the variables were log-transformed, excepting RISr.

size, variables of population may be applicable as substitutes of industrial sizes when predicting the influences on air quality.

Although urbanization involves processes related to both pollution and environmental treatment, more negative effects are demonstrated in this research. During urbanization, pollution increases due to more intensive building construction, energy consumption and transportation, but greater environmental investments are also made possible by increased population and economic power. In this paper, our analyses indicate that urbanization had more negative than positive effects on air quality in Chinese cities. However, the total independent contribution was only 1.7%, relatively small compared to the pollution group. Considering that the effects of urbanization on air quality are indirect and that different urbanization policies and planning might imply different influences, further researches on more systematic analyses of urbanization effects should be conducted.

“Coverage of green space in built-up area” was demonstrated to be the most important positive variable for air quality in urban China. This finding is in agreement with some earlier reports. Urban vegetation was found to play an important role in decomposing and mitigating air pollution by Beckett et al. (1998) and Nowak and Crane (2000). Additional vegetation cover in urban areas may decrease the concentrations of air-pollutants and their outflow by reducing energy demand and biogenic emissions in surrounding areas (Civerolo et al., 2000). However the significance of the air-pollutant uptake by urban vegetation has been questioned by other researchers. Escobedo and Nowak (2009) reported that less than 2% of particles with a diameter of 10 microns or less (PM_{10}) were removed in areas with the highest tree cover (26%). After all, our results suggest that improving green space is an important approach to improve air quality in Chinese

cities. However, since a correlation does not necessarily prove a cause and an effect, other factors which were not analyzed in this study may influence the effect of green space on air quality.

However, another significant index of green space, the “area of green space in parks” was negatively related to air quality, which tends to support the remarks of Escobedo and Nowak (2009). The ecological functions of green spaces in cities are complex (Pataki et al., 2011). In China, most green spaces in parks are relatively artificial and intensively cultivated (Zhao et al., 2010b). To attract more visitors, park management often plant novel alien plants and large areas of lawn, which require a great amount of maintenance and thus lead to much more energy consumption and pollution emissions. Managers should therefore encourage the growth of more natural vegetation, especially trees, to improve the ecological functions of park green spaces.

The contribution of environmental investment to air quality was surprisingly low. It is possible that this is due to a time lag effect, after which the benefits of the investment begin to exhibit. To inspect time lag effects, environmental investments were analyzed with air quality of each of the three years following the investments. As shown in Table 5, environmental investment as percentage of GDP contributed only 1% yet significantly, to the variance in AOFDAQ-A after one year. However, the effects increased during following years, and had doubled by the third year after the investments were made. It seems that the existence of a time lag effect is therefore confirmed. To evaluate the contribution of environmental investments to air quality, time lag effects should be accounted for.

The relatively weak effects of environmental investments may also be attributed to the inadequate intensity and efficiency of investment. Although environmental protection has become an important concern for the national government, as a densely populated developing country, it is difficult for China to find the right balance between economic development and environmental protection (Fang et al., 2009). Although the environmental investments by cities above prefecture level increased from 1.6 ± 2.6 (average $\pm$ standard deviation) billion yuan in 2002 to 2.6 ± 5.2 billion yuan in 2007, the amount of environmental investment remains relatively low, and greater and more effective investment may be required to achieve better results. Moreover, the investment pattern may also be important to efficiently improve air quality. Because the air quality index used in this paper treated various pollutants as equally important, if only some of the pollutants were targeted by pollution control efforts, other high concentration pollutants might still decrease the air quality value (API).

Other factors that were not discussed in this paper may also contribute to overall air quality, including meteorological conditions (Barman et al., 2008; Cermak and Knutti, 2009; Wang et al., 2009; Ren et al., 2011), topographical influences, emission sources (Wang et al., 2010), transport from the stratosphere and long-range transport (Zhao et al., 2010a). Further examination of all these variables could improve ability to predict variance in air quality. In

Table 4
Results of multi-linear regression of AOFDAQ-A.

Model	Label for variables	Un-standardized coefficients	Standardized coefficients	Collinearity statistics VIF (variance inflation factor)	Sig.
		B value	Beta		
(Constant)		58.671			<0.001
Population in building industry sector ^a	b_1	5.908	0.140	3.098	0.026
Coverage of green space in built-up area ^a	b_2	20.103	0.196	1.114	<0.001
Ratio of industrial solid wastes utilized ^a	b_3	6.276	0.201	1.183	<0.001
Ratio of industrial SO_2 removed	b_4	0.002	0.250	1.056	<0.001
Total supply of coal gas ^a	b_5	−2.529	−0.243	1.344	<0.001
Population in mining sector ^a	b_6	−7.505	−0.219	1.133	<0.001
Population in transport, storage and post sectors ^a	b_7	−4.256	−0.311	3.269	<0.001
Population density ^a	b_8	−2.505	−0.145	1.112	<0.001

^a Variables are ln-transformed.

Table 5

Linear regression results of environmental investments with different span of time lag.

Time lag	Adjusted R^2	p -value	pr value of Levene's test	Slope
Three years	0.0202	0.0023	1	0.6096
Two years	0.0136	0.0104	0.9995	0.5826
One year	0.0108	0.02	0.9611	0.5992
Zero year	0.011	0.0193	0.9137	0.7248

addition, air quality is only one of the factors describing the environmental quality of a city, so studies on other environmental risks may be important for the overall environmental quality and sustainable development of cities.

5. Conclusion

By sampling cities covering most provinces in mainland China, it was found that air quality improved during the period 2000–2009. By linear regression, 21 significant variables were identified from 72 possible explanatory variables, and the relative effects on air quality were quantified. With an independent contribution of 16.6%, the pollution group had a primary influence on air quality (AOFDAQ-A). All the five indexes of urbanization exhibited

a negative relationship with air quality. Among the independent variables, “population of mining subsector” and “coverage of green space in built-up area” were respectively the most significant negative and positive explanatory variables, both contributing more than 12% of explained variance in AOFDAQ-A. However, environmental investments show time lag effects and did not have a large contribution to explain variance in AOFDAQ-A. Finally, when applied with caution, air quality studies in general would benefit from a wider application of partitioning methods. Whether the variation in air quality is ultimately more causally related to the significant variables would be further confirmed by experimental work or by accumulating information from other similar study settings.

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Appendix A

Table A.1

List of sampled long-term monitoring cities in China.

City	Province	Monitoring periods	City	Province	Monitoring periods
Beijing	Beijing	2000–2009	Jining	Shandong	2004–2009
Tianjin	Tianjin	2000–2009	Taian	Shandong	2004–2009
Shijiazhuang	Hebei	2000–2009	Rizhao	Shandong	2004–2009
Qinhuangdao	Hebei	2001–2009	Zhengzhou	Henan	2000–2009
Taiyuan	Shanxi	2000–2009	Kaifeng	Henan	2004–2009
Datong	Shanxi	2004–2009	Pingdingshan	Henan	2004–2009
Yangquan	Shanxi	2004–2009	Wuhan	Hubei	2000–2009
Changzhi	Shanxi	2004–2009	Jingzhou	Hubei	2004–2009
Huhehaote	Neimenggu	2000–2009	Changsha	Hunan	2000–2009
Chifeng	Neimenggu	2004–2009	Changde	Hunan	2004–2009
Shenyang	Liaoning	2000–2009	Zhangjiajie	Hunan	2004–2009
Dalian	Liaoning	2000–2009	Guangzhou	Guangdong	2000–2009
Anshan	Liaoning	2004–2009	Shaoguan	Guangdong	2004–2009
Fushun	Liaoning	2004–2009	Shenzhen	Guangdong	2000–2009
Changchun	Jilin	2000–2009	Zhuhai	Guangdong	2000–2009
Haerbin	Heilongjiang	2000–2009	Shantou	Guangdong	2000–2009
Qiqihaer	Heilongjiang	2004–2009	Zhanjiang	Guangdong	2000–2009
Mudanjiang	Heilongjiang	2004–2009	Nanning	Guangxi	2000–2009
Shanghai	Shanghai	2000–2009	Liuzhou	Guangxi	2004–2009
Nanjing	Jiangsu	2000–2009	Guilin	Guangxi	2001–2009
Suzhou	Jiangsu	2000–2009	Beihai	Guangxi	2001–2009
Nantong	Jiangsu	2000–2009	Haikou	Hainan	2000–2009
Lianyungang	Jiangsu	2001–2009	Chengdu	Sichuan	2000–2009
Yangzhou	Jiangsu	2004–2009	Chongqing	Chongqing	2000–2009
Zhenjiang	Jiangsu	2004–2009	Zigong	Sichuan	2006–2009
Hangzhou	Zhejiang	2000–2009	Luzhou	Sichuan	2004–2009
Ningbo	Zhejiang	2001–2009	Deyang	Sichuan	2004–2009
Wenzhou	Zhejiang	2000–2009	Mianyang	Sichuan	2004–2009
Huzhou	Zhejiang	2004–2009	Nanchong	Sichuan	2006–2009
Shaoxing	Zhejiang	2004–2009	Guiyang	Guizhou	2000–2009
Hefei	Anhui	2000–2009	Kunming	Yunnan	2000–2009
Wuhu	Anhui	2004–2009	Qujing	Yunnan	2004–2009
Fuzhou	Fujian	2000–2009	Yuxi	Yunnan	2004–2009
Xiamen	Fujian	2000–2009	Xi'an	Shanxi	2000–2009
Quanzhou	Fujian	2004–2009	Baoji	Shanxi	2004–2009
Nanchang	Jiangxi	2000–2009	Weinan	Shanxi	2004–2009
Jiujiang	Jiangxi	2004–2009	Lanzhou	Gansu	2000–2009
Jinan	Shandong	2000–2009	Xining	Qinghai	2000–2009
Qingdao	Shandong	2000–2009	Yinchuan	Ningxia	2000–2009
Zibo	Shandong	2004–2009	Shizuishan	Ningxia	2004–2009
Zaozhuang	Shandong	2004–2009	Urumqi	Xinjiang	2000–2009
Yantai	Shandong	2000–2009	Kalamayi	Xinjiang	2004–2009
Weifang	Shandong	2004–2009			

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