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WHAT CAUSES DIFFERENCES IN PM2.5 CONCENTRATION IN CHINA? STRUCTURES ARE MORE IMPORTANT

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ABSTRACT

This paper studies the effects of factors such as economic growth, industrial structure and governance on the differences in PM2.5 concentration among groups by using Oaxaca-Blinder (OB) decomposition and Recentered Influence Function (RIF) regressions. Specifically, we first explore the differences in PM2.5 concentration among cities and find that structure effects attributable to differences in returns to these factors contribute more to total difference in PM2.5 concentration than composition effects caused by differences in the means of these factors. Moreover, the offsetting effects of positive composition and negative structure effects drag the time trend of PM2.5 concentration downward. Besides, the negative impact of GDP per capita on PM2.5 concentration implies the existence of an inverted U-shaped environmental Kuznets curve (EKC) between PM2.5 concentration and GDP per capita. In sum, we find that the differences in returns to factors or structures of cities are the main causes of differences in PM2.5 concentration among cities in China compared to the differences in the means of factors.

Contribution/Originality: This paper contributes to the existing literature by exploring the main causes behind the differences in PM2.5 by using OB decomposition and Recentered Influence Function (RIF) regressions and demonstrates that structure effects are the most important in accounting for the total differences in PM2.5 among cities.

1. INTRODUCTION

PM2.5 has become a significant public concern due to its negative effects on climate change (e.g. (Kan, Chen, & Tong, 2012; Tai, Mickley, & Jacob, 2010)) and human health (see (Hueglin et al., 2005; Zhang et al., 2020)). For example, PM2.5 (fine particles with diameter of less than 2.5 micrometer) can enter deeply into the lung , destroy the alveolar wall and causes dysfunction in the lung, which consequently lead to serious respiratory and cardiovascular diseases (see (Li, Yang, Song, Chen, & Ou, 2016; Xing, Xu, Shi, & Lian, 2016)). Thus, understanding the causing factors is important for preventing the pollution and improving the air quality which benefits human health.

There is a plenty of literature focusing on the driving factors of PM2.5 from different perspectives. From social and economic perspective, many studies find that urbanization (Xu & Lin, 2016), income or GDP per capita (Ji, Yao, & Long, 2018), energy intensity (Xu, Luo, & Lin, 2016), coal consumption, transportation (Hao & Liu, 2016), population density (Ding et al., 2019; Luo et al., 2017), industrial structure (Chen et al., 2020; Ji et al., 2018; Yang et al., 2018) and so on, have significant impact on PM2.5 concentration. Moreover, Cheng, Li, and Liu (2017) use dynamic spatial panel models to analyze the impact of FDI (Foreign direct investment) on PM2.5 concentration. Wu, Zhang, and Ding (2020) examine the relationship between R&D and PM2.5. In view of natural science, lots of literature focuses on the impacts of meteorological conditions on PM2.5 concentration. Those conditions including temperature, rainfall, pressure, wind, planetary boundary layer and so on are closely related to the PM2.5 concentration. For instance, Zhao, Chen, Sun, and Shi (2018) study the effects of meteorological conditions on PM2.5 and find that temperature and rainfall affect PM2.5 negatively and pressure has a positive impact on the PM2.5 concentration. Liu et al. (2020) show that increase in the speed of wind can effectively reduce PM2.5 concentration. Miao et al. (2019) study the interaction between planetary boundary layer and PM2.5 concentration. Having figured out the above driving factors, a number of researches have concentrated on finding the effective ways of reducing PM2.5 concentration such as improving energy efficiency (Fu & Li, 2020) and using clean energy. In addition, another effective way in controlling PM2.5 concentration is government governance which includes increasing green coverage rate (Chen, Dai, Yang, & Zhu, 2019) domestic garbage harmless disposal rate (Shi, Zhang, Zhou, & Wang, 2020) output value of products made from waste gas, waste water & solid wastes and controlling industrial emission of waste gas.

Identifying the effects of those factors mentioned above can not only help us figure out the potential factors driving the PM2.5 concentration but also evaluate the efficiency of government measures. Lyu et al. (2016) investigate the impacts of driving factors on the variation of air pollution in China from 1997 to 2012, by using the Logarithmic Mean Divisia Index method and demonstrate the decomposition results multiplicatively and additively. Currie, Voorheis, and Walker (2020) analyze the difference in exposure to PM2.5 between non-Hispanic white and non-Hispanic black by using Oaxaca-Blinder (OB) decomposition (Blinder, 1973; Oaxaca, 1973).

We contribute to the literature in the following three ways. Firstly, to the best of our knowledge we are the first to explore the main causes behind the differences in PM2.5 across cities from the perspectives of industrial structure, government governance and economic development. Secondly, we find that the main causes behind the differences in PM2.5 are the structure effects but not composition effects. Structure effects are usually caused by unmeasured factors which could be related to the PM2.5 concentration. For example, in decomposing wage gaps between male and female, we usually ascribe positive structure effects to gender discrimination since the existence of gender discrimination could cause return to education larger for male than for female even if both have same education level and other same characteristics (Fortin, Lemieux, & Firpo, 2011). Here we describe the unmeasured characteristics/relations as structures of society (e.g. wage discrimination between male and female). Similarly, in this research we denote the unmeasured characteristics/relations in the cities as the structures of the cities. Thirdly, our findings reveal that there are offsetting effects in composition and structure effects across time in China. Lastly, we apply Recentered Influence Function (RIF) regressions (proposed by Firpo, Fortin, and Lemieux (2009)) to decompose quantile difference in PM2.5 and show that the main conclusion from results in mean difference decomposition is robust.

The rest of the paper is organized as follows. Section 2 outlines the empirical methods, and Section 3 describes the data and results. We conclude in Section 4.

2. METHODOLOGY

Before we proceed to the decomposition process of difference in PM2.5, we first briefly introduce the traditional OB decomposition and RIF regression. The goal of these two methods is to decompose the difference in means or quantiles of dependent variable between two groups into structure effects and composition effect.

2.1. OB Decomposition

Before analyzing the decomposition effects, we first define some notations. Let t index the groups, Y_{it} is the PM2.5 of city i in group t. The gov_{it}, ind_{it}, and ec_{it} represent the factors related to the government governance, industrial structure and economic growth of city i in group t which are explained in section 3 and t is the error term. We use the following Equation 1 to represent the mathematical relation between PM2.5 and factors above.

$$Y_{it} = \alpha_{0t} + ecg_{it}\beta_{t,ecg} + ind_{it}\beta_{t,ind} + gov_{it}\beta_{t,gov} + \epsilon_{it} \quad (1)$$

Where: $E(\epsilon_t|X) = 0$ and $X = (\alpha_0, ecg, ind, gov)'$ is a $(K+1) * 1$ vector of independent variables. Note that ecg, ind, gov are the three vectors which include different variables (see Section 3). The coefficients β denote returns to factors. Suppose $t = 1$ be the indicator of group 1, then by the law of iterated expectation, the overall effects can be represented as :

$$\begin{aligned}
\Delta_o &= E(Y|t=1) - E(Y|t=0) \\
&= E[E(Y|t=1, X)|t=1] - E[E(Y|t=0, X)|t=0] \\
&= E(X|t=1)'\beta_1 + E(\epsilon_t|t=1) - E(X|t=0)'\beta_0 + E(\epsilon_t|t=0) \\
&= \overline{X_1'\beta_1} - \overline{X_1'\beta_0} + \overline{X_1'\beta_0} - \overline{X_0'\beta_0} \\
&= \underbrace{\overline{X_1'}(\beta_1 - \beta_0)}_{\Delta_S\text{:Structure effects}} + \underbrace{(\overline{X_1'} - \overline{X_0'})\beta_0}_{\Delta_C\text{: Composite effects}} \\
&= \underbrace{\textstyle\sum_{k=1}^{K+1}\left(\overline{X_{1k}}(\beta_{1k} - \beta_{0k})\right)}_{\Delta_{S_k}} + \underbrace{\textstyle\sum_{k=1}^{K+1}(\overline{X_{1k}} - \overline{X_{0k}})\beta_{0k}}_{\Delta_{C_k}} \quad (2)
\end{aligned}$$

Where: $\overline{X_{tk}}$ refers to the mean of kth covariate of group t. From Equation 2, we can do decomposition by using equation estimated for $t = 1$ and equation estimated for $t = 0$. The structure effects Δ_S indicate differences in coefficients across the groups and could be induced by unmeasured characteristics that differ across groups. The composite effects Δ_C present the importance of differences in means of variables across groups. Furthermore, the detailed structure componentΔ_{S_k}can be explained as the effect of difference in coefficients $(\beta_{1k} - \beta_{0k})$ that is associated with x_k and detailed composition component Δ_{C_k}can be interpreted as the effect of difference in the means of x_k between group 1 and group 0; such as $(\overline{X_{1k}} - \overline{X_{0k}})\beta_{0k}$. In this paper, $t = 1$ denotes the group of cities with high PM2.5 and $t = 0$ the group of cities with low PM2.5. Or, $t = 1$ denotes the group of cities surveyed from 2011 to 2018 and $t = 0$ represents the group of cities surveyed from 2000 to 2010.

2.2. RIF-Regression Method

A RIF-regression is simply a standard regression with the dependent variable being replaced by the Recentered Influence Function of the statistic of interest. RIF-regression is quite related to distribution regression (Chernozhukov, Fernández-Val, & Melly, 2013; Foresi & Peracchi, 1995) as we show below[1]. The influence function corresponding to a variable Y for the quantile is given by $(\tau - 1\{Y \le Q_\tau\})/f_Y(Q_\tau)$, where : $1\{Y \le Q_\tau\}$ is an indicator function which is equal to 1, otherwise zero. $f_Y(Q_\tau)$ is the density of the marginal distribution of Y and Q_τ is the population τ-quantile of the unconditional distribution of Y. Then, the recentered influence function for τ-quantile can be written as :

$$RIF(y, Q_\tau) = Q_\tau + \frac{\tau - 1\{y \le Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau} \cdot 1\{y \le Q_\tau\} + c_{2,\tau} \quad (3)$$

Where: $c_{1,\tau} = -1/f_Y(Q_\tau)$ and $c_{2,\tau} = Q_\tau + \tau/f_Y(Q_\tau)$. RIF is just an indicator variable $1\{y \le Q_\tau\}$, except the constants $c_{1,\tau}$ and $c_{2,\tau}$. This makes the RIF-regression very similar to the distribution regression. To

[1]A distribution regression with the linear probability model as the link function is simply a linear regression of $1\{y \le Q_\tau\}$ on X.

obtain RIF, we first compute the sample quantile Q_τ and estimate the density at Q_τ using kernel methods. Then, an estimate of the RIF of each observation is obtained by plugging in the estimates of the sample quantile $\widehat{Q_\tau}$ and the density at $\widehat{Q_\tau}$ into the Equation 3.

In the paper, Y_{it} is the mean value of PM2.5 for city i in group t. We can estimate $\widehat{RIF_{it}}(Y_{it}, Q_\tau)$ by using $\widehat{RIF_{it}}(Y_{it}, Q_\tau) = \widehat{Q_\tau} + \frac{\tau - 1\{Y_{it} \le \widehat{Q_\tau}\}}{\widehat{f_Y}(\widehat{Q_\tau})}$. We, then, regress $\widehat{RIF_{it}}(Y_{it}, Q_\tau)$ on the factors as follows :

$$\widehat{RIF_{it}}(Y_{it}, Q_\tau) = \beta_{0t} + ecg_{it}\beta_t + ind_{it}\beta_t + gov_{it}\beta_t + \epsilon_{it} \tag{4}$$

Where, ecg, ind, gov are three vectors of independent variables for individual i in group t, $\widehat{RIF_{it}}(Y_{it}, Q_\tau)$ is the Recentered Influence Function for τ-quantile which can be estimated by Equation 3 and β are the vectors of coefficients of independent variables.

Then the RIF-regression version of the Oaxaca-Blinder decomposition for any unconditional τ-quantile follows the similar way as in the OB decomposition by replacing $E(Y|t)$ with $\widehat{RIF_{it}}(Y_{it}, Q_\tau)$ of group t.

3. DATA AND RESULTS

3.1. Data

PM2.5 dataset and independent variables studied in this paper are obtained from the Atmospheric Composition Analysis Group at Dalhousie University and the China City Statistical Yearbook. This dataset includes 285 cities surveyed from 2000 to 2018.

In the paper, we consider two kinds of differences in PM2.5 concentration. We take the logarithm of PM2.5. The first one is the difference in PM2.5 concentration between cities with high PM2.5 and cities with low PM2.5. The second one is the differences in PM2.5 concentration between cities surveyed in 2000-2010 and 2011-2018 separately. More specifically, we first analyze the sample cross-sectionally by taking the average of PM2.5 concentration across all years (2000-2018) and then dividing the sample into two groups -- High PM2.5 and Low PM2.5 groups. Thus, we have 143 cities in the High PM2.5 and 142 in the Low PM2.5 groups, respectively. We have also separated the sample according to the time period. To be specific, we have taken cities surveyed in 2000-2010 as the 2000-2010 group and cities surveyed in 2011-2018 as the 2011-2018 group. We note that these two groups include same cities but surveyed in different time periods. Figure 1 plots the density of different groups.

Next, we briefly discuss the independent variables studied in the paper. Basically, we include three kinds of factors: The first one is related to industrial structure, the second one is government governance and third one is economic development.

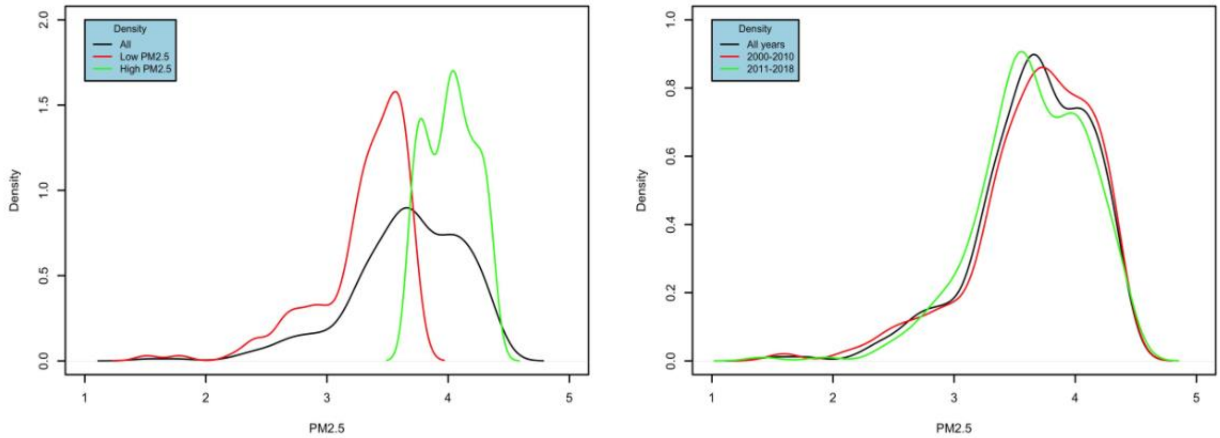


Figure 1. Density of PM2.5

Notes: The figure plots densities of PM2.5 concentration. The left panel represents the densities ofaverage PM2.5 of the High and Low groups and all year sample. The right panel plots the densities of average PM2.5 of the 2000-2010, 2011-2018 and all years sample.

3.1.1. Industrial Structure

We use the proportion of secondary industry in GDP (psi) and the proportion of service sector in GDP (pss) to represent industrial structure. In China, Manufacture industry is the main sector of secondary industry and contributes greatly to the PM2.5 concentration. With the development of economy, service sector gradually replaces the energy intensive industry and thus the PM2.5 concentration decreases (Ji et al., 2018).

3.1.2. Government Governance

Following Shi et al. (2020) government governance can be categorized into two groups—self-governance and public governance. We add common industrial solid wastes utilized ratio (ciswur) and centralized treatment rate of sewage treatment plant (ctrstp) into the self-governance group. Both factors have negative impact on PM2.5 concentration. Moreover, we put green covered rate of completed area (gcrca) and domestic garbage harmless disposal rate (dgaca) into the group of public governance. Chen et al. (2019) show that increase in gcrca can reduce PM2.5 concentration.

3.1.3. Economic Development

GDP represents the level of economic development GDP per capita (inc) and population density (pd) represents the level of economic development. The higher the inc and pd, greater will be the economic activities which cause air pollution (Shi et al., 2020). Besides, it is common that more industrial activities mean more industrial emission of waste gas such as nitrogen oxide (ieno) and sulfur dioxide (iesdio) that result in more PM2.5 concentration. Also more industrial enterprises above the designated size, the higher the degree of urban economic development is.

Table 1 defines the variables studied in the paper and Table 2 while Table 3 summarizes the statistics of the variables for High vs Low PM2.5 groups and 2000-2010 vs 2011-2018 groups, respectively. From Table 2, the mean values of most independent variables such as ciswur, ctrstp, dgaca, gcrca, ieno, iesdio, psi and pd are larger for the High group than the counterparts in the Low group. However, the Low group has higher mean value of pss and gpc. In Table 3, by comparing the 2000-2010 group with the 2011-2018 group, the difference in mean values of PM2.5 between two groups is -0.03. Although it is not statistically significant but implies that PM2.5 concentration tends to decrease over time and thus shifts the whole distribution to the left (from red one to green one) as shown in the right panel of Figure 1. In other words, the time trend of PM2.5 concentration tends to be downward. Besides, the values of variables except gpc are all larger for the group surveyed in 2011-2018 than the one surveyed in 2000-2010.

Table 1. Abbreviations of variables.

No.	Variables	Definition
1	PM2.5	Average exposure to PM2.5
2	CISWUR	Common industrial solid wastes utilized ratio
3	CTRSTP	Centralized treatment rate of sewage treatment plant
4	DGACA	Domestic garbage harmless disposal rate
5	GCRCA	Green covered rate of completed area
6	IENO	Industrial emission of nitrogen oxide
7	IESDIO	Industrial emission of sulfur dioxide
8	PSS	Proportion of service sector in GDP
9	PSI	Proportion of secondary industry in GDP
10	GPC	GDP per capita
11	PD	Population density

Table 2. Summary statistics of high and low PM2.5 group.

Variables	Low PM2.5		High PM2.5		Difference	
	Mean	SD	Mean	SD	Mean	SD
PM2.5	3.30	0.39	4.02	0.20	0.72	0.04
CISWUR	71.56	20.23	84.83	13.04	13.27	2.01
CTRSTP	65.71	11.00	70.76	9.43	5.05	1.21
DGACA	79.53	13.53	83.04	11.97	3.51	1.51
GCRCA	34.93	10.45	36.62	4.71	1.69	0.96
IENO	26315.64	28552.31	36981.32	53384.15	10665.68	5076.49
IESDIO	50614.10	43113.45	69474.91	64457.13	18860.81	6500.57
PSS	38.16	8.02	36.49	7.08	-1.68	0.90
PSI	45.99	10.79	49.05	8.27	3.06	1.14
GPC	33296.86	22833.29	33099.62	20287.27	-197.24	2558.17
PD	291.90	314.58	549.28	271.01	257.37	34.77

Table 3. Summary statistics of 2000-2010 and 2011-2018 groups.

Variables	Low PM2.5		High PM2.5		Difference	
	Mean	SD	Mean	SD	Mean	SD
PM2.5	3.67	0.50	3.64	0.46	-0.03	0.04
CISWUR	76.62	20.84	80.09	19.16	3.47	1.68
CTRSTP	50.00	16.93	85.48	10.03	35.48	1.17
DGACA	69.17	22.53	91.94	9.86	22.77	1.46
GCRCA	32.89	9.64	39.67	7.31	6.78	0.72
IENO	24958.12	21942.24	39511.33	84061.47	14553.21	5146.21
IESDIO	63130.83	61575.31	57095.84	54398.02	-6034.99	4866.88
PSS	35.98	7.57	39.43	8.60	3.45	0.68
PSI	46.95	10.81	48.34	9.43	1.39	0.85
GPC	19875.05	14668.78	50082.81	30841.22	30207.76	2022.99
PD	415.13	316.08	433.88	336.31	18.75	27.34

3.2. Results

In this section, we show the decomposition results for mean and quantile differences in PM2.5 between two kinds of groups: high vs low PM2.5 groups and 2000-2010 vs 2011-2018 groups. By using OB decomposition we obtain the mean overall effects, aggregate structure, aggregate composition effects and detailed effects attributable to specific variables. We also apply RIF regression to decompose the quantile differences into composition and structure effects.

We first show decomposition results for the mean differences in Table 4 and then show results for quantile differences in PM2.5 (Figure 2 and Figure 3).

Table 4. Aggregate and detailed decomposition of mean differences in PM2.5.

Variables	High vs Low			2000-2010 vs 2011-2018		
	OE	**CE**	**SE**	**OE**	**CE**	**SE**
All	0.722**	0.190**	0.532**	-0.026***	0.192*	-0.217*
CISWUR	0.176	0.063**	0.113	0.079	0.020***	0.058
CTRSTP	0.359	0.030***	0.330	0.392	0.297*	0.096
DGACA	-0.530	-0.009***	-0.521	-0.110	-0.021**	-0.089
GCRCA	-0.155	-0.004***	-0.150	-0.037	-0.001**	-0.036
IENO	0.032**	-0.004***	0.036**	-0.019**	-0.000***	-0.019**
IESDIO	-0.068*	0.004***	-0.072*	-0.013**	-0.006***	-0.008**
PSS	-0.333	0.014**	-0.347	0.556	0.003**	0.553
PSI	-0.476	0.006***	-0.482	0.512	0.020***	0.492
GPC	0.096*	0.001***	0.095*	0.002**	-0.132**	0.133**
PD	0.126*	0.090**	0.036*	-0.032**	0.010***	-0.043**

Note: OE denotes overall effects, CE composition effects and SE structure effect. All denotes aggregate. *p<0.1; **p<0.05; ***p<0.01.

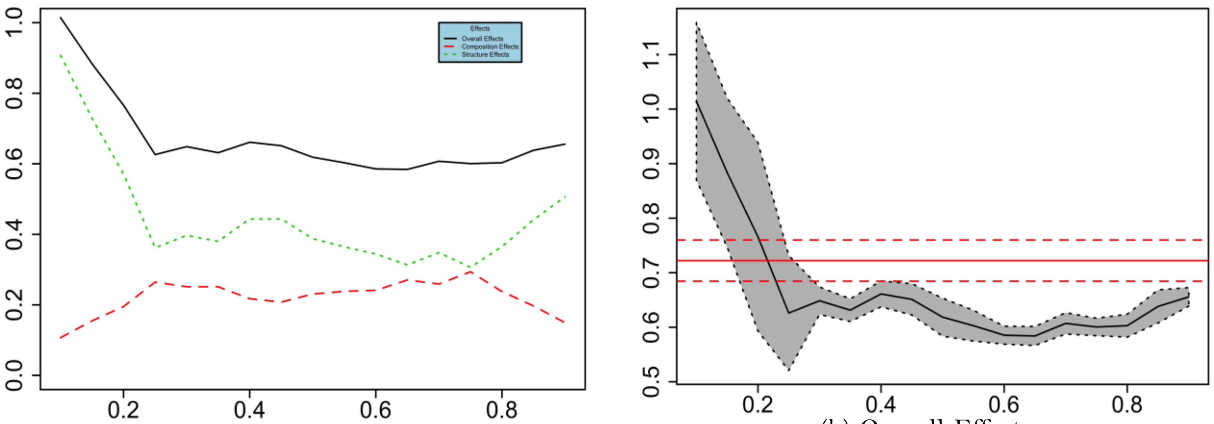
3.3. Mean Differences

3.3.1. High vs Low PM2.5 Groups

The left panel of Table 4 shows the detailed decomposition effects for the mean differences in PM2.5 between high and low PM2.5 groups. We first see that the overall difference is 0.72, aggregate composition effect 0.19 and structure effect 0.53. This means that 74% of difference in mean PM2.5 is contributed by the differences in coefficients of factors and only 26% of differences is attributed by the differences in means of factors across these two groups. This is of great interest because it indicates that high PM2.5 is more related to the factors associated with PM2.5 concentration compared with differences in the means of factors studied in this paper. That is to say, the structure effects might be due to unmeasured characteristics of cities that differ across the groups and that are related to PM2.5 concentration.

Secondly, the component which has the largest positive effects is ctrstp (common industrial solid wastes utilized ratio) which contributes positively to the difference in PM2.5 concentration and most of the contribution is from structure effect ($\Delta_{s,ctrstp}$ in Equation 1. It means that the return to ctrstp in cities with high PM2.5 is much higher than the one in cities with low PM2.5. This could be caused by the structures of cities or other unmeasured variables. Thus, exploring differences in returns to ctrstp between cities with high and low PM2.5 concentration seems to be a very interesting research for further study. Besides, we also find that dgaca and psi are two largest components with negative structure effects which decrease the differences in PM2.5 concentration.

Lastly, it is also interesting to note that pd (population density) across groups is the most important factor in aggregate composition effects. Positive composition effects ($\Delta_{c,pd}$ in Equation 1 plus positive differences in the mean values of pd implies the sign of its coefficient is positive. This could be explained in two sides.



(a) All Effects (b) Overall Effects

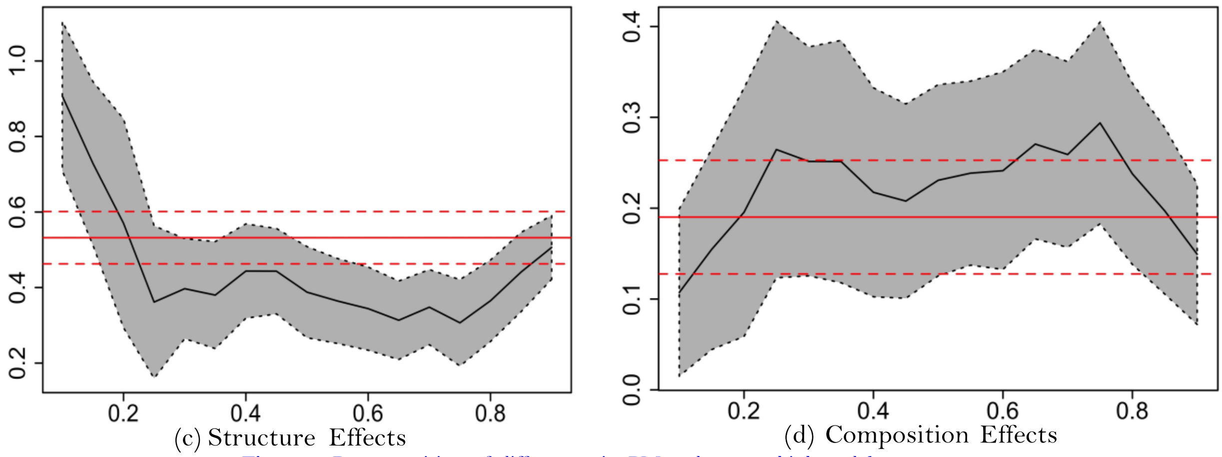


Figure 2. Decomposition of differences in PM2.5 between high and low groups.

Notes: The figure plots aggregate decomposition results across quantiles. Panel (a) plots overall, structure and composition effects across quantiles. Panel (b), (c), (d) plots overall, structure and composition effects with 95% confidence bands for differences in mean (in red)and quantiles of PM2.5.

First, higher population density is usually followed by urbanization and industrialization which usually produce more pollution (Hao & Liu, 2016). Second, more people mean more consumption of energy such as coal. On the contrary, dgaca (domestic garbage harmless disposal rate) plays the most important role in narrowing the gap of PM2.5 concentration in CE. Together with the situation that group with higher PM2.5 has higher value of dgaca (see Table 2), we conclude that the return to dgaca has negative effects on PM2.5 concentration. In China, the main ways of garbage disposal are sanitary landfill and incineration. Sanitary landfill has the advantage of producing gases used in clean energy production. As compared to landfill, incineration has some advantages; such as occupying less land and easy handling (Ma, Cao, Lu, Ding, and Zhou, 2016). In addition, in the process of burning, incineration can produce heat which could be used to generate power and decrease the coal consumption. Therefore, dgaca has a negative impact on PM2.5 concentration by producing clean energy and decreasing coal consumption. From left panel of Table 4, there is another factor which has significant negative impact on gap in PM2.5 concentration–gcrca.

In sum, we find the difference in PM2.5 between cities with high and low PM2.5 is more contributed by the differences in returns to factors (structure) but less by the differences in the means of factors across two groups (composition).

3.3.2. 2000-2010 VS 2011-2018 Groups

The right panel of Table 4 shows detailed decomposition results for 2000-2010 and 2011-2018 groups. Firstly, we see that the overall difference (-.0255) is negative but very small, that is the PM2.5 concentration in China decreases slowly over time. Note that the aggregate composition effect (Δ_c in Equation 1 is actually positive and the structure effect Δs in Equation 1 is negative. That being said, the differences in means of some factors increase differences in PM2.5 concentration but the differences in returns to some factors decrease gaps in PM2.5 concentration over time. As for this situation, we conjecture the reason is that China puts more efforts on reducing air pollution and improves the structures of cities related to PM2.5 concentration which are more friendly to PM2.5.

Secondly, we realize that ctrstp, pss and psi tend to increase the differences in PM2.5 concentration over time but through different channels.

For instance, most part of composition effects is due to differences in the means of ctrstp, which could positively affect differences in PM2.5 concentration. From Table 3, mean value of ctrstp for group surveyed in 2011-2018 is larger than that in 2000-2010 which implies the return to ctrstp has positive effect on PM2.5 concentration. In other words, ctrstp can lead to the increase of PM2.5 because (1) waste water material can be aerosolized and emit into the air (Upadhyay, Sun, Allen, Westerhoff, & Herckes, 2013) and (2) waste water treatment will consume lots of electric energy which cause air pollution (Capodaglio & Olsson, 2020).

Accounting for most part of structure effects, gpc is the most important variable which has negative impact on shrinking the gap of PM2.5 concentration. This suggests an inverted Ushaped environmental Kuznets curve (EKC) exists between PM2.5 concentration and GDP per capita. In the early stages of economic development, increase~~s~~ in the pollution concentration tends to decrease the environmental quality, but after GDP per capita reaching at specific level, economic development improves the quality of environment (Stern, 2017).

However, for pss and psi, the differences in the returns to these two factors contribute most although the structure effects are not statistically significant. In sum, we find that over time PM2.5 tends to decrease, and the reason is from the changes in returns to factors but not from changes in factors themselves. We believe that a detailed exploration of changes in structures of cities needs further research.

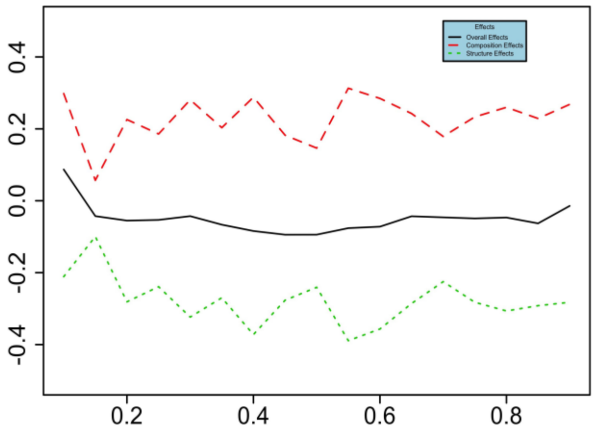
3.4. Quantile Differences

Figure 2 shows aggregate decomposition results for quantile differences in PM2.5 between high and low PM2.5 groups. Panel (a) plots the overall, aggregate structure and composition effects. The three effects are all positive across the quantiles.

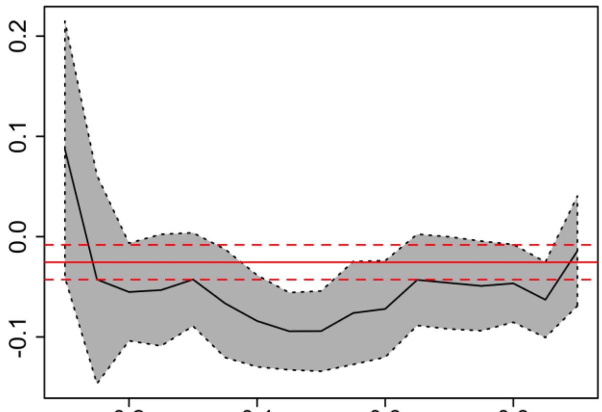
The trends of overall and aggregate structure effects are opposite to that of aggregate composition effects below 25th and above 75th quantiles. Moreover, it is evident to see that the line of structure effects is above that of composition effects. In other words, structure effects are larger than composition effects across the whole quantiles and thus account for the maximum portion of overall effects. From Fortin et al. (2011) structure effects have also been called "unexplained" part of the PM2.5 differentials and could be induced by model specification and unmeasured factors or structures of cities. Panel (b), (c) and (d) plot 95% confidence bands for each of three aggregate effects in Panel (a) respectively. We can see that for most quantiles the effects are statistically significant.

Figure 3 shows aggregate decomposition results for quantile differences in PM2.5 between 2000-2010 and 2011-2018 groups. Panel (a) shows that the overall effects are around zero. The aggregate composition effects are positive across quantiles; whereas the aggregate structure effects are negative. This implies that aggregate composition effects tend to enlarge the gap in PM2.5 concentration over time but the structure effects have the opposite effect and tend to narrow that gap. As mentioned in the previous section, the structure effects could be caused by unmeasured factors and model specification.

One reason could be the time effect since the 12th Five-Year Plan implemented at the beginning of 2011, makes more stringent policies to control environmental pollution. Panel (b), (c) and (d) demonstrate 95% confidence bands for the three effects separately and show that they are statistically different from zero for some quantiles. Although the most effects are not statistically significant, we still can find that composition and structure effects are positively and negatively correlated to the overall effects respectively.



(a) All Effects



(b) Overall Effects

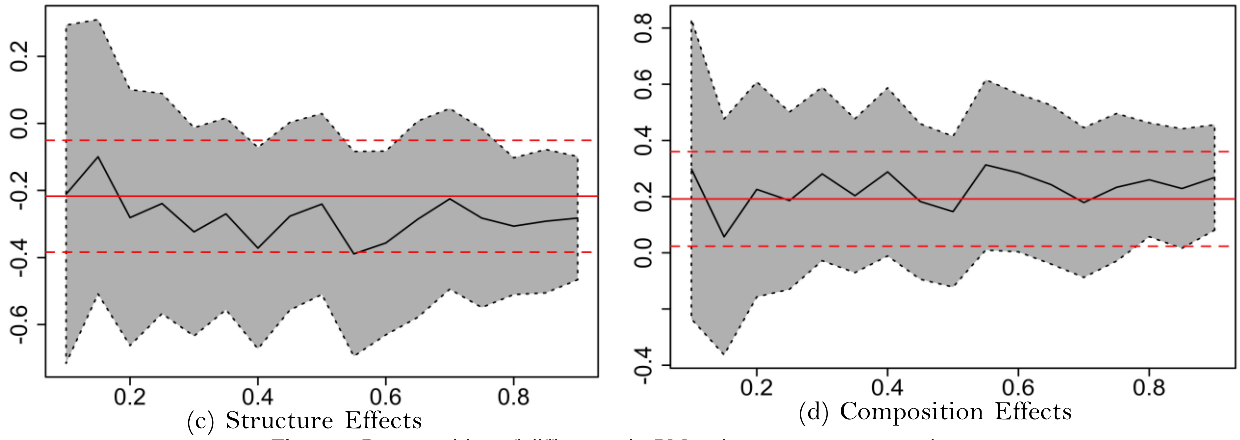


Figure 3. Decomposition of differences in PM2.5 between 2000-2010 and 2011-2018.

Notes: The figure plots aggregate decomposition results across quantiles. Panel (a) plots overall, structure and composition effects across quantiles. Panel (b), (c), (d) plots overall, structure and composition effects with 95% confidence bands for differences in mean (in red)and quantiles of PM2.5.

4. CONCLUSION

In the paper, we decompose the differences in PM2.5 concentration among cities by using OB decomposition and RIF regressions. Firstly, we separate cities into two groups, one with high PM2.5 and one with low PM2.5, to study why cities have different PM2.5 concentrations. We find that compared to composition effects, structure effects or structures of cities are the main reason causing the differences in PM2.5 concentration between groups through making different returns to factors (such as ctrstp) across groups. Also differences in the means of pd have the largest composition effects and thus tend to expand the differentials of PM2.5 concentration. Moreover, we cut entire sample 2000-2018 into two groups, 2000-2010 and 2011-2018 to study the difference in PM2.5 over time. We find that overall effect is negative which means that there exists a small decrease in PM2.5 over time. The main reason is the offsetting effects between composition and structure effects. Specifically, there is positive composition but negative structure effects. In other words, the differences in the means of factors tend to increase differences in PM2.5 (positive composition effect) but differences in the returns to factors decrease differences in PM2.5 concentration (negative structure effect) over time. Differences in the means of ctrstp account for the major portion of composition effects which increase differences in PM2.5 concentration. gpc is the largest component which has negative composition effects. This means the coefficient or return to gpc is negative which suggests an inverted U-shaped environmental Kuznets curve (EKC) exists between PM2.5 emissions and GDP per capita. Lastly, we find that the main conclusion for mean differences is robust to most of quantiles. Based on the results, we suggest the following two directions for further research. First, it is worth examining the mechanisms behind differences in structures (returns to factors) among cities and the time trend of changes in structures. Second, it is straightforward to study more factors, including some geographic and meteorological factors, other than the ones studied in this research.

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