Analysis of Factors Influencing PM$_{2.5}$ in Beijing: A Microcosmic and Dynamic Perspective for Sustainable Development

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Abstract. Haze pollution has become a hot issue concerned with the process of modernization and one serious problem requiring urgent solution, especially in Beijing. PM$_{2.5}$ is the main reason causing haze and its harm. Although there has been research centering on factors affecting PM$_{2.5}$, little attention has been devoted to the microcosmic and dynamic effects on it. Vector auto-regression (VAR) mode is applied in this study to explore the interaction between PM$_{2.5}$, PM$_{10}$, SO$_2$, CO and NO$_2$. Results of Granger causality tests tell that there exists causal relationship between PM$_{10}$, SO$_2$, CO, NO$_2$ and PM$_{2.5}$. Impulse response functions (IRFs) show that the response of PM$_{2.5}$ to a shock in CO is positive and large in the short period, while the reaction of PM$_{2.5}$ to a shock in SO$_2$ increases over time. Meanwhile, variance decomposition indicate that PM$_{2.5}$ is more closely related to CO in the short term while SO$_2$' influence accounts for a higher proportion in the long run. The findings provide a novel perspective to analyze the factors influencing PM$_{2.5}$ dynamically and contribute to a better understanding of haze and its relationship with sustainable development.

1. Introduction

Nowadays, air pollution has been a big problem for people's normal work, life and health, from which Beijing has a narrow escape. Air pollution in Beijing may be more serious than that in other cities, and haze weather in recent years is a critical factor causing severe environmental crisis and has caused widespread concern [1].

The biggest source of haze in the air is what is called PM (Particulate Matter) particles, which are divided into PM$_{10}$ and PM$_{2.5}$ according to their diameter sizes [2]. The smaller the particles are, the more tenacious their vitality is and they can do more harm to human beings. Furthermore, they can invade the body with people's breathing and cause harm to the human body. In 2012, particles whose diameter is less than 2.5 micrometers were collectively referred to as ‘the fine particulate matter’ by the U.S. environmental protection agency, also known as PM$_{2.5}$ [3]. The average width of the fine particles reaches about one of 30 points of human hair. Because of their extremely small size, they can be deep into the lungs and therefore do much harm to human health. Ten years’ studies have shown long-term exposure to PM$_{2.5}$ can cause cardiovascular mortality rate increased by 6%-13% [4].

With haze increasingly rampant, the research and governance on haze has become a global work. Cheng et al. studied characteristic of particulate matter in Alberta cities, founding that the contribution
of various pollutants is different, but on the whole vehicle emissions and fuel combustion play important roles [5]. Sawant et al. specifically analyzed the chemical composition of PM$_{2.5}$ in Southern California, with results showing that the region's concentration of elemental carbon OC is much higher than that in other cities, which is critical to the region's high concentration of PM$_{2.5}$ [6]. Matthew’s research about PM$_{2.5}$ components indicated that sulfur compounds are the main components of PM$_{2.5}$ and the sulphide is largely decided by the concentration of SO$_2$ [7]. David et al. (2013) identified the major sources of PM$_{2.5}$ and their impact on environmental and human health [1]. Cox analyzed PM$_{2.5}$ and Air Pollutants using regression analysis [3], while there is research assessing the health and economic value of the smog pollution, lacking causes and prevention measures [8].

Previous studies on PM$_{2.5}$ are mainly limited to macro level. Our studies offer an important original contribution to examining the factors affecting PM$_{2.5}$ from the microcosmic and dynamic perspective. Vector auto-regression model combing with IRFs and variance decomposition is established to explore the interaction between PM$_{10}$, CO, SO$_2$, NO$_2$ and PM$_{2.5}$, hoping to provide theoretical foundation and experience for future governance of haze in Beijing.

2. Empirical Analysis

2.1 Data

China has started to implement new air quality index (AQI) since January 2014, and PM$_{2.5}$ is included in the calculation of AQI [9]. Indicators are concentration of PM$_{2.5}$, PM$_{10}$, CO, SO$_2$ and NO$_2$ and corresponding data is extracted from the AQI monitoring system and covers the period of January 1, 2014 to December 31, 2014. Correlation coefficient matrix is calculated to indicate the correlation among these indicators and we find that correlation coefficients are all above 0.5, some even are close to 0.9, indicating there exists positive and significant correlations between PM$_{2.5}$, PM$_{10}$, CO, SO$_2$ and NO$_2$. Consequently, it is necessary to analyze the interplay among them.

2.2 Empirical Methodology

We begin our empirical analysis by VAR mode to estimate the interactions between PM$_{2.5}$, PM$_{10}$, CO, SO$_2$ and NO$_2$. We then address several econometric issues that might arise in this study, namely Granger causality tests, Impulse Response Functions and Variance decomposition.

The advantages of VAR approach to traditional regression are in the following: First, it treats all variables as joint endogenous without any prior constraints, exploring the bidirectional causality between all variables. Secondly, the mode takes lagged effects into consideration, each endogenous variable can be the function of all variables lag item. Third, it can illustrate the effects of a shock in one variable on others applying IRFs and variance decomposition [10].

The general form of the VAR model is as follows:

$$
\mathbf{PM}_{t} = \begin{bmatrix} C_{PM_{2.5}} \\ C_{PM_{10}} \\ C_{CO} \\ C_{SO_2} \\ C_{NO_2} \end{bmatrix} + \sum_{q=1}^{Q} \begin{bmatrix} \alpha_{11}^{t-q} & \alpha_{12}^{t-q} & \cdots & \alpha_{15}^{t-q} \\ \alpha_{21}^{t-q} & \alpha_{22}^{t-q} & \cdots & \alpha_{25}^{t-q} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{51}^{t-q} & \alpha_{52}^{t-q} & \cdots & \alpha_{55}^{t-q} \end{bmatrix} \begin{bmatrix} PM_{2.5-t-q} \\ PM_{10-t-q} \\ CO_{t-q} \\ SO_{2-t-q} \\ NO_{2-t-q} \end{bmatrix} + \mathbf{\varepsilon}_{t},
$$

(1)

Where PM$_{2.5}$ denotes the concentration of PM$_{2.5}$ in t. Q represents the order of the model, which can be determined by using Akaike's information criterion (AIC). We calculate AIC for each model and determine the optimal lag length 2 according to the principle of the minimum AIC [11]. Next, Granger causality test is used to analyze the causal relationship between pairs of variables, such as testing whether CO is the cause of PM$_{2.5}$.

The VAR model is also supplemented with IRFs and Variance decomposition to elaborate the dynamic relationship between variables. IRFs are used to examine the response of one variable to a
3. Results
To conduct both Granger causality and VAR analysis, the variables must be stationary. Results of the test indicate that all variables are stationary. Granger causality tests also indicate that the joint variables have causal relationship. This supports our approach of analyzing the variables as a full dynamic system through VAR analysis.

3.1. VAR Regression Results
VAR model is conduct to study the interaction between SO$_2$, CO, NO$_2$, PM$_{10}$ and PM$_{2.5}$. The VAR equation is as follows:

$$
\begin{align*}
& PM_{2.5} \\
& PM_{10} \\
& SO_2 \\
& CO \\
& NO_2
\end{align*}
$$

We can see that PM$_{2.5}$ has positive relationship with itself in short-term supported by the positive and significant coefficient 0.85 on the first lag. CO has a short-term positive relationship with PM$_{2.5}$, which is shown by the positive and significant coefficient on the first lag and insignificant coefficient for the second lag. On the first lag, the relationship between SO$_2$ and PM$_{2.5}$ is insignificant. However, the coefficient is significant as time goes by and reaches 0.76 in the second lag. Besides, the influence of NO$_2$ on PM$_{2.5}$ declines with time going by. In addition, PM$_{2.5}$'s influence on PM$_{10}$ is positive and significant. Meanwhile, PM$_{10}$ has positive relationship with itself on the first lag. Just as the influence imposing on PM$_{2.5}$, CO has a short-term positive relationship and the influence of SO$_2$ on PM$_{10}$ can be manifested until the second lag. Besides, the influence of NO$_2$ on PM$_{10}$ is significant on the first lag and declines with time going by. When it comes to the results with CO, SO$_2$ and NO$_2$ as dependent variables, we find that none of them are significantly influenced by PM$_{2.5}$ or PM$_{10}$.

3.2. Impulse Response Functions
We supplement the regression estimates with the analysis of IRFs. Although each variable in the system can be used as a response variable to the impact of the other variables, we focus on PM$_{2.5}$’s response to other variables. IRFs in our study can be understood as: the response of PM$_{2.5}$ to a shock in PM$_{10}$, SO$_2$, CO and NO$_2$ respectively. The IRFs results are as follows:

![Response of PM$_{2.5}$ to PM$_{10}$](image1)

![Response of PM$_{2.5}$ to PM$_{1.0}$](image2)
Figure 1 shows the response of PM$_{2.5}$ when PM$_{10}$, SO$_2$, CO and NO$_2$ are given a change of a standard deviation. In the first period, a positive change of PM$_{2.5}$ gives itself the biggest shock, which reaches nearly 51.32%. With time goes on, the impulse decreases gradually and reaches the lowest (-2.88%) in the 5th period, then the shock begins to rise and in the 10th period reaches 0.42%. When PM$_{10}$ changes a standard deviation, it has impact on PM$_{2.5}$ by 45% in the 1st period. Then the change of PM$_{10}$ influence on PM$_{2.5}$ is falling to minimum -3.2% until the 5th period and reaches slowly 0.25% in the 10th period.

When SO$_2$ suddenly gets a shock of a positive standard deviation, the initial impact on PM$_{2.5}$ is 30.8%. From the 2nd period the impact is reduced until reaches to a minimum of 1.98% in the tenth period. The impact of a standard deviation of NO$_2$ on PM$_{2.5}$ in the 1st period is 38.75%, after a rapid decline in the 4th period it reaches 3.33%. In next few periods the impact of changes in NO$_2$ is negative, but in the 8th period it returns to the positive and remains at the level of around 0.4%. A positive impact of CO on PM$_{2.5}$ in the 1st phase is 43.03% and has a rapid decline to 7.8% in the 3rd period, in the later three periods the impact is negative. In the 7th period it returns to 0.44% and have change little in the later periods, remaining 0.63% in the 10th period.

It is evident that in the 1st period PM$_{2.5}$’s reactions to other variables are all relatively large, the biggest impact is that by itself, which reaches 51.32%. As time goes by, the influence of variables on PM$_{2.5}$ is reduced, but the degree of reduction is not the same. Generally speaking, in the first four periods the impact of the changes in each variable on PM$_{2.5}$ is large and decreases quickly over time. Starting from the 5th period, other variable’s impact on PM$_{2.5}$ is relatively small, which marginally increases until the 10th time period. This can be understood utilizing a superimposed effect: Today’s PM$_{2.5}$ is not only affected by today’s SO$_2$, CO and NO$_2$, but by yesterday, the day before yesterday and even a few days ago. This is in accordance with the actual situation, when a certain substance concentration increase, it immediately exerts impact on PM$_{2.5}$, and over time this influence is gradually reduced but still plays a part.

From the IRFs results it is also obvious that among SO$_2$, CO and NO$_2$, CO imposes the biggest impact on PM$_{2.5}$ in the 1st period. The increase of CO in the air will lead to PM$_{2.5}$’s immediate and sharp increase, and the impact of NO$_2$ takes the second place, followed by the influence of SO$_2$ on
PM$_{2.5}$ which is relatively small. Their impact on PM$_{2.5}$ however is declining over time, and the impact of CO decreases faster. In the tenth period, the influence of SO$_2$ on PM$_{2.5}$ is still larger (1.98%), the impact of CO on PM$_{2.5}$ is 0.63%, and NO$_2$’s influence is minimum (0.27%). Overall, CO has a greater impact on PM$_{2.5}$ in the initial stage, while the influence of SO$_2$ on PM$_{2.5}$ sustains a long time.

3.3. Variance Decomposition

Variance decomposition is used to study the contribution of other variables to the variance variation of PM$_{2.5}$. Results of Variance decomposition are as follows:

| Table 1. Variance decomposition results of PM$_{2.5}$ (%) |
|-------------|-------------|-------------|-------------|-------------|-------------|
| Period      | S.E         | PM$_{2.5}$  | PM$_{10}$   | SO$_2$      | CO          | NO$_2$      |
| 1           | 51.32       | 15.75       | 12.03       | 36.08       | 34.81       | 1.32        |
|             | (1.53)      | (1.47)      | (3.57)      | (2.99)      | (0.80)      |             |
| 2           | 63.55       | 17.77       | 11.51       | 34.00       | 30.85       | 5.85        |
|             | (2.36)      | (2.25)      | (4.54)      | (3.33)      | (2.03)      |             |
| 3           | 66.56       | 18.60       | 10.54       | 33.53       | 28.11       | 9.20        |
|             | (2.87)      | (2.43)      | (4.99)      | (3.66)      | (3.00)      |             |
| 4           | 68.01       | 18.35       | 10.23       | 32.58       | 28.62       | 10.20       |
|             | (3.09)      | (2.44)      | (5.22)      | (4.29)      | (3.499)     |             |
| 5           | 68.68       | 18.08       | 10.11       | 32.10       | 29.55       | 10.14       |
|             | (3.17)      | (2.47)      | (5.47)      | (4.70)      | (3.63)      |             |
| 6           | 68.95       | 17.96       | 10.04       | 32.01       | 29.91       | 10.07       |
|             | (3.21)      | (2.49)      | (5.67)      | (4.82)      | (3.65)      |             |
| 7           | 69.09       | 17.90       | 10.00       | 32.14       | 29.95       | 10.06       |
|             | (3.23)      | (2.51)      | (6.05)      | (4.91)      | (3.61)      |             |
| 8           | 69.19       | 17.86       | 9.97        | 32.14       | 29.95       | 10.06       |
|             | (3.25)      | (2.54)      | (6.05)      | (4.91)      | (3.61)      |             |
| 9           | 69.25       | 17.83       | 9.95        | 32.19       | 29.94       | 10.06       |
|             | (3.27)      | (2.55)      | (6.22)      | (4.95)      | (3.60)      |             |
| 10          | 69.30       | 17.81       | 9.94        | 32.23       | 29.94       | 10.05       |
|             | (3.29)      | (2.57)      | (6.38)      | (5.00)      | (3.58)      |             |

As shown in Table 1, the variance change of PM$_{2.5}$ can be separately decomposed to these factors consisting of PM$_{2.5}$, PM$_{10}$, SO$_2$, CO and NO$_2$, giving us a detailed analysis of these factors contribution to PM$_{2.5}$’s variance changes: In the 1st stage, PM$_{2.5}$ by itself explain the change of variance accounting for 15.75%, with PM$_{10}$ accounting for 12%, SO$_2$ explaining 36.08%, CO explaining 34.8% and NO$_2$ with 1.3%. As time goes on, PM$_{2.5}$ variance change by itself shows slow decrease, and in the 10th period stabilizes at 17.8%; With time passes by, PM$_{2.5}$’s variance change explained by PM$_{10}$ is in slow decline and falls to 9.9% in the 10th period; The change of PM$_{2.5}$’s variance caused by SO$_2$ has always been at the highest level and reaches 32.2% in the 10th period; PM$_{2.5}$’s variance change caused by CO has also been gradually decreased but still maintains the higher level (30%); Meanwhile, the variance change of PM$_{2.5}$ explained by NO$_2$ has gradually increased from the original 1.3% and in the 10th period been steadied at around 10%.

Just as IRFs, SO$_2$ and CO explain the most of the variance of PM$_{2.5}$. NO$_2$’s impact on the variance change of PM$_{2.5}$ gradually increases over time, this may be because the proportion of SO$_2$ and CO on PM$_{2.5}$ change in the variance is reduced, which leads to an increase the proportion of NO$_2$’s explanation. On the whole, the analysis results of variance decomposition are in accordance with that
in the impulse response functions, SO$_2$ and CO have the greater influence on PM$_{2.5}$, followed by the effects of NO$_2$.

4. Conclusions
In this paper, Vector auto-regression (VAR) mode together with Granger causality tests, Impulse Response Functions and variance decomposition is utilized to verify the interaction between PM$_{2.5}$, PM$_{10}$, SO$_2$, CO and NO$_2$. Results are in the following: Granger causality tests manifest that there exists causal relationship between PM$_{2.5}$, PM$_{10}$, SO$_2$, CO and NO$_2$. SO$_2$, CO and NO$_2$ are influential factors of PM$_{2.5}$ and PM$_{10}$, namely, the increase of PM$_{2.5}$ and PM$_{10}$ concentration in Beijing has certain relationship with the increase of concentration of SO$_2$, CO and NO$_2$. Impulse response results show that the response of PM$_{2.5}$ to a shock in CO is positive and large in the short term, while the elasticity of PM$_{2.5}$ with respect to SO$_2$ increases over time. As time progresses, PM$_{2.5}$ becomes more sensitive to the shift in SO$_2$. Meanwhile, Variance decomposition results indicate that PM$_{2.5}$ is more closely related to CO in short term, while SO$_2$’s influence accounts for a higher proportion in the long run. Besides, NO$_2$’s contribution to PM$_{2.5}$ is an added process, the effect of NO$_2$ began to be embodied as the extension of lag. These findings provide new view to analyze the dynamic influence factors of PM$_{2.5}$ and contribute to a better understanding of haze and its relationship with sustainable development.

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