

# Correlations between air pollutant emission, logistic services, GDP, and urban population growth from vector autoregressive modeling: a case study of Beijing

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**Abstract** Logistics in China has grown rapidly; in 2015, the freight volume has reached 41 billion ton, increasing by 4.4% year-on-year. At the same time, the pollutant emissions from freight cars account for 70% of total emissions of motor vehicles, which severely affected the air quality. The purpose of this paper is to investigate the effect of logistics on air pollution; we used a new methodology based on vector autoregression of freight turnover, gross domestic product, and urban population. We selected Beijing as our test and created a model using time series data for the period 2000–2014. In this model, permanent residents, freight turnover, and SO<sub>2</sub> emission were used as proxies for population size, logistic services, and degree of air pollution. Our analyses showed that the expansion of logistic services had the biggest effect on air pollution. Moreover, impulse response analysis revealed that logistic growth caused more serious air pollution over a short time, with an ongoing negative effect. GDP growth was only weakly correlated with air pollution, while urban population growth appeared to have little effect.

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## 1 Introduction

As the increasing of haze weather, the problem of air pollution control has become the most noteworthy livelihood issue in China. Airborne hazardous substances not only result in environmental pollution, but also affect human health. In order to reduce the air pollution, the Chinese government has introduced many policies such as The Action Plan For the Control of Air Pollution since September 2013 and Law of the People's Republic of China on the Prevention and Control of Atmospheric Pollution 2015. Despite the many control measures taken, air pollution in China is extremely serious, especially in industrial cities, developed areas, and metropolises. Thus, it is necessary to find out the factors which cause the air pollution. It is pointed by The Chinese Academy of Sciences that the two main causes of air pollutant emission are coal combustion and automobile exhaust. Zhao et al. (2011) indicated that the potential of air quality improvement due to structure adjustment in power plants and heating sectors is limited in Beijing. However, many large cities have reduced their use of coal and turned their industrial focus to the service industry. Logistics related to this industry are an important support for urban operations. However, few studies focus on the impact of such logistic services on air pollution. The rapid development of China's economy as well as the daily demand of its increasing population has increased the circulation of goods. For example, in 2015, the freight turnover in China reached 17368.9 billion ton-kilometers. However, such logistics involve heavy transportation stress, forming an important proportion of the total urban automobile use. It is pointed out by 2015 China's Motor Vehicle Pollution Control Report that combustion of fossil fuels during transportation is a main source of air pollution. Meanwhile, the report on government's work pointed out that in 2015 China's emissions of SO<sub>2</sub> were going to reduce by 3%. These have caused the government to restrict the time of out-of-town lorries in cities and to plan to adopt EP-type automobiles instead of diesel trucks to reduce emissions. More recently, the Chinese metropolitan governments suppressed population size because increasing population will bring more traffic pressure and cause more energy consumption and air pollution. Beijing, as atypical service-oriented city in China, has a large scale of logistics, with a rapidly growing GDP and large population. Based on a preliminary calculation, the permanent residents and the GDP of Beijing were 21.52 million and 2133 billion CNY in 2014. Logistic services play a support role in its economic development, the added value of transportation and warehouse industries accounts for around 94.8 billion CNY in 2014. Meanwhile, according to the air pollution index, air pollution in Beijing reached a peak in November 2015, having the most dangerous level in recent years. Thus, we select Beijing as our test to instigate this study. The VAR (vector autoregressive) model takes the form of multiple simultaneous equations, and the endogenous variables in each equation form a regression with the lagged values of all endogenous variables to estimate the dynamic relationships between all the endogenous variables. Moreover, it allows us to consider both long-run restrictions and short-run restrictions. Considering the characteristics of model and available data, we use a VAR model to estimate relationships between key variables to explore the effect of growth in GDP, population, and logistics on air pollution.

Air pollutant emission has been discussed extensively from an economic perspective. Grossman and Krueger (1991) found that SO<sub>2</sub> and “smoke” concentrations increase with

per capita GDP for low levels of national income, but decrease with GDP growth at higher levels of income. Such results are confirmed by Selden and Song (1994) and Kaufmann et al. (1998). Selden et al. evaluated the environmental Kuznets curves (EKC) for emissions of four important air pollutants using international data. Their results showed that all four pollutants exhibited inverted-U relationships with per capita GDP, consistent with the EKC hypothesis. Similarly, Kaufmann et al. demonstrated that there was a U-shaped relationship between income and atmospheric concentration of SO<sub>2</sub>. However, Akbostanci et al. (2009) explored the relationship between income and air pollution using data from 1992 to 2001 for Turkish provinces. Their results did not support the EKC hypothesis. Saidi and Mbarek (2016) examined the impact of financial development, income, trade openness, and urbanization on CO<sub>2</sub> emissions in 19 emerging economies. Results showed a positive monotonic relationship between income and CO<sub>2</sub> emissions. None of their models supported the EKC hypothesis. Farhani and Ozturk (2015) found a positive monotonic relationship between real GDP and CO<sub>2</sub> emissions in Tunisia. Likewise, Fodha and Zaghdoud (2010) found that there was a long-term relationship between the per capita emissions of CO<sub>2</sub> and SO<sub>2</sub> and the per capita GDP in Tunisia. In contrast, Fosten et al. (2012) found support for the inverse U-shaped relationship between CO<sub>2</sub> and SO<sub>2</sub> emissions and GDP. Other studies explored an even wider range of economic variables. Kiviyiro and Arminen (2014) examined co-integration relationships between CO<sub>2</sub> emissions, energy consumption, economic development and foreign direct investment in six sub-Saharan African countries. Dogan and Turkekul (2016) found that there was bidirectional causality between CO<sub>2</sub> emission and GDP in the USA. Zakarya et al. (2015) found that foreign direct investment had a co-integration relationship with CO<sub>2</sub> emission in BRICS countries (Brazil, Russia, India, China, and South Africa). Al-mulali (2012) found that total primary energy consumption, foreign direct investment net inflows, GDP, and total trade were important factors in increasing CO<sub>2</sub> emission in various countries. Jovanović et al. (2015) explored the impact of agro-economic factors on greenhouse gas emissions in European developing and advanced economies. Asongu et al. (2015) used an autoregressive distributed lag approach to examine the nexus between energy consumption, CO<sub>2</sub> emissions, and economic growth in 24 African countries. Their findings showed that there was a long-term relationship between energy consumption, CO<sub>2</sub> emissions, and GDP. Salahuddin et al. (2016) estimated short- and long-term effects of Internet usage and economic growth on CO<sub>2</sub> emissions in Australia. Their findings indicated that a higher level of economic growth was associated with a lower level of CO<sub>2</sub> emissions. Studies carried out in China (e.g., Wang et al. 2016) show support for an inverted U-shaped relationship between economic growth and SO<sub>2</sub> emission. Alper and Onur (2016) investigated the validity of the EKC hypothesis for the period between 1977 and 2013. Wang et al. (2015) undertook a decomposition study of energy-related CO<sub>2</sub> emissions from industrial and household sectors during 1996–2012; their results showed that the expansion of economic activity was the dominant stimulatory factor for the increase in CO<sub>2</sub> emissions in China. Hao and Liu (2014) investigated the relationship between FDI, foreign trade, and CO<sub>2</sub> emissions. Hao et al. (2015) found that per capita GDP was positively correlated with per capita SO<sub>2</sub> emission.

Few studies have explored the influence of logistic growth related to goods and services on the environment. Zhao et al. (2014) established a SO<sub>2</sub> emission measurement model for provincial-scale logistics in China. Their study found that the SO<sub>2</sub> emission of unit freight turnover for provinces in the western region was higher than for provinces in the east. Tian et al. (2014) examined different regions' freight turnover and energy consumption with respect to various transport modes (i.e., railway, highway, waterway, aircraft, and oil

pipeline) in China between 2000 and 2011. This study showed that the two highest transport modes in terms of the greenhouse gas emission intensity were aircraft and highway. Liao et al. (2011) estimated that the CO<sub>2</sub> emission from Taiwan container transport during 1998–2008, using a multiple regression model. Their analyses showed that GDP and oil price were key factors affecting CO<sub>2</sub> emissions. Yang et al. (2013) proposed a bilinear non-convex mixed-integer programming model to help city logistic operators cut their CO<sub>2</sub> emissions by around 54.5%. More generally, Wang et al. (2014) analyzed major technology and policy barriers to improve China's transport energy output. Xiao et al. (2015) found that the energy intensity and carbon intensity of logistics related to industry remained at high levels. Liu et al. (2015) analyzed the CO<sub>2</sub> emission differences among China's four transport sub-sectors. Xu and Lin (2015) used a vector autoregressive (VAR) model to analyze the factors affecting changes in CO<sub>2</sub> emissions in the transport sector. Their results showed that reducing private vehicles had more impact on emission reduction than reducing cargo turnover. Thus, logistics related to industry clearly affect the environment, especially air quality. However, there is no clear understanding of how air pollution reflects growth in freight turnover, GDP, and permanent residents.

VAR models have been widely used in environmental contexts. Yu and Liu (2015) investigated the relationship between six standards of the air quality index in Wu Han using a VAR model. Yang et al. (2009) explored the dynamic character of correlated economic variables with air pollution. Soytaş et al. (2007) investigated the effect of energy consumption and output on carbon emission in the USA. Xu and Lin (2016) used a VAR model to analyze the influence of the changes in CO<sub>2</sub> emissions in the industry sector. In this study, impulse response analysis and variance decomposition also are used to explore relationships between economic variables and air pollutant emissions.

## 2 Materials and methods

### 2.1 Vector autoregression model

The VAR model can be used to analyze the dynamic interaction of time series and the dynamic impact of random disturbances on the variable system. As such, it explains the influence of various impacts on variables, and it is one of the relatively extensive applications in multivariate time series models. It can easily handle multiple variables and dynamically analyze their statistical properties. We used the VAR model to dynamically analyze the influence of freight turnover, GDP, and population size on SO<sub>2</sub> emission.

The mathematical expression of a general VAR (P) model is:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t \quad t = 1, 2, \dots, T, \quad (1)$$

where  $y_t$  is a  $K \times 1$  vector of time series  $t = 1, 2, \dots, T$ ;  $A$  is a  $K \times K$  parametric matrix;  $x_t$  is a  $D \times 1$  vector of exogenous variables; and  $B$  is the  $K \times D$  coefficient matrix to be estimated.  $\varepsilon_t$  represents the random error term, while  $p$  represents the lag period.

Akaike information criterion (AIC) and Schwarz Criteria (SC) are used to select the lag periods of the VAR model in this study. The AIC and SC are computed as follows:

$$AIC = -2l/T + 2n/T, \quad (2)$$

$$SC = -2l/T + n \ln T/T, \quad (3)$$

where  $n$  represents the total number of estimated parameters and  $T$  represents the sample length.  $l$  is determined using:

$$l = -\frac{Tk}{2}(1 + \ln 2\pi) - \frac{T}{2} \ln \left| \sum \hat{\cdot} \right|. \quad (4)$$

In practice, the unit root test is used to measure the stationary case, while the co-integration test is used to check whether any correlations exist. If the VAR model is stable, then our analysis can continue with an impulse response analysis and variance decomposition.

## 2.2 Data

Logistics is a general designation, covering many activities, such as freight transportation, distribution, and packaging, related to supply and demand of products or services. Because we aimed to study the effect of logistics on air pollution, freight transportation was selected as its proxy. Freight transport involves production of a number of harmful gases, contributing to air pollution; freight turnover is its most useful data descriptor. Freight turnover addresses not only the amount of transportation targets, but also their transportation distances, comprehensively showing the size of urban logistics. In 2014, the freight turnover in Beijing reached 67.28 billion ton-kilometers. Air pollutants related to freight transport include the harmful substances: nitrogen oxide, sulfur oxides, and particulate matter. Sulfur dioxide (SO<sub>2</sub>) is a pollutant recorded as part of air quality measurements in the city with complete data and some papers showed the relationship between logistics service and SO<sub>2</sub> emissions. Zhao et al. (2014) established a SO<sub>2</sub> emission measurement model for provincial-scale logistics in China. Their study found that the SO<sub>2</sub> emission of unit freight turnover for provinces in the western region was higher than for provinces in the east. Xu et al. (2011) analyzed the SO<sub>2</sub> emissions from China's railway transport from 1975 to 2007. Their study found that SO<sub>2</sub> emissions from railway transportation were getting reduced gradually for 33 years. Thus, sulfur dioxide was selected to be representative of harmful substances in the air. Moreover, the permanent residents are an urban population. To have practical significance, this study selected the fastest economic growth period of Beijing, covering from 2000 to 2014, with information sourced from the Beijing Social Development Database. To reduce the differences among values of variables and heteroscedastic effects, logarithmic processing was carried out on all data; thus, freight turnover is given as LOGF and SO<sub>2</sub> emission as LOGS, GDP as LOGG, and population size as LOGP.

## 3 Results

### 3.1 Unit root test results

Before using the VAR model, it was necessary to guarantee the stationary data to prevent spurious regression. Table 1 shows the results of augmented Dickey–Fuller unit root tests. Our results show that the null hypothesis was not rejected. In fact, while all the variables are first-order difference stationary, rejection of the null hypothesis occurs at the 10% level. Thus, it can be concluded that all the variables are first-order difference stationary, and can proceed with co-integration test.

### 3.2 Co-integration test results

Since most time series of variables are non-stationary, the transformed time series often do not have direct economic significance. Engle and Granger (1987) proposed the co-

**Table 1** ADF unit root test results

Variable	ADF test statistic	Prob.	1% Level	5% Level	10% Level	Conclusion
LOGF	-0.687084	0.8191	-4.004425	-3.098896	-2.690439	No stationary
DLOGF	-2.984.39	0.0704*	-4.297073	-3.212696	-2.747676	Stationary
LOGG	1.287212	0.9997	-4.992279	-3.875302	-3.388330	No stationary
DLOGG	-3.749014	0.0601*	-4.992279	-3.875302	-3.388330	Stationary
LOGP	-1.805951	0.3614	-4.057910	-3.119910	-2.701103	No stationary
DLOGP	-2.866796	0.0837*	-4.297073	-3.212696	-2.747676	Stationary
LOGS	0.403647	0.9750	-4.004425	-3.098896	-2.690439	No stationary
DLOGS	-2.745937	0.0903*	-4.057910	-3.119910	-2.701103	Stationary

D represents the first difference of variables

\* 10% significant level

**Table 2** Cointegration test results

Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	Max-Eigen statistic
None*	0.988486**	103.7394**	58.03473
At most 1*	0.927321**	45.70470**	34.08220
At most 2	0.563886	11.62250	10.78807
At most 3	0.062171	0.834433	0.834433

\* 10% significant level

\*\* 5% significant level

integration theory and methods, providing another way for non-stationary series modeling. The co-integration test is used on multiple variables. Although they may have independent long-term variation, if they are co-integrated, then there exists a long-term and stable relationship between these variables (e.g., Xu and Lin 2015). We use the method of multivariate co-integration proposed by Johansen and Juselius (1990), based on the VAR model, and our co-integration tests are carried out on data, using the first-order lag. Test results are shown in Table 2.

Trace statistics show that at the confidence level of 95%, there are two long-term co-integration relationships between freight turnover, SO<sub>2</sub> emission, population, and GDP.

### 3.3 Construction of our model

A VAR model is built based on the statistical properties of the data. It is constructed by taking each endogenous variable in the system as the lag value function of all the endogenous variables in the system. In this way, a single-variable autoregression model is expanded to a “vector” autoregression model, comprising a multivariate time series variable.

An important aspect of the VAR model is the determination of lag order. The bigger the lag period, the greater the need for estimated parameters, and the greater the reduction in the degrees of freedom of the model, while an insufficient lag period will not reflect the dynamic characteristics of the model. AIC and SC are used to evaluate lag order in this study. Lag order for our VAR model is given in Table 3, reflecting AIC and SC.

**Table 3** Lag length test results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	58.08565	NA	2.86e−09	−8.320869	−8.147038	−8.356599
1	135.8155	95.66753	2.54e−13	−17.81777	−16.94862	−17.99642
2	189.0616	32.76682*	2.51e−15*	−23.54794*	−21.98346*	−23.86951*

\* Lag order selected by the criterion

Estimates, along with their *t* values and standard errors, are given in Table 4. Clearly, the equation has high R-square values.

To ensure our model was well-specified, it was necessary to conduct a stability test. If the VAR model is not stable, then an impulse response analysis cannot be carried out. Stability was assessed using an autoregressive characteristic polynomial. When all the characteristic roots are less than 1, i.e., they are located within the unit circle, then the model is stable. VAR roots of this characteristic polynomial are shown in Fig. 1.

### 3.4 Impulse response functions

Because the VAR model is not a theoretical model, no apriority constraint is made on the variables. Thus, the dynamic effect on the system is analyzed as the VAR model is impacted. The impulse response function is an analysis tool used by many researchers to describe this causality, i.e., the shock generated by the change of one variable in the VAR model on another variable (e.g., Xu and Lin 2015; Aydin and Cavdar 2015). Analyses are presented dynamically using graphs, which show the response direction, amplitude, and persistence of the variables in the model related to a shock. Such changes can be observed over time. Its advantage is to highlight variable changes over time at a system-scale, i.e., when the whole system undergoes external shocks, it will be temporarily unstable, but will achieve balance with adjustments over time. In impulse response analysis, the VAR model is transformed into a vector process of infinite order. All other conditions are unchanged. Thus, the error term impacted by a unit at some time point will impact the endogenous variable in the model during the current period.

To analyze the influence of freight turnover, GDP, and population size on SO<sub>2</sub> emission, a one-standard-deviation shock was given using these three variables in turn. The resulting impulse response functions for SO<sub>2</sub> emission are shown in Fig. 2. Here, the horizontal axis shows that the lag period of impact effect is 30. The vertical axis shows the response of SO<sub>2</sub> emission to these three factors; the solid line is the impulse response function, and the dotted line gives ±2 standard deviations to the response.

Figure 2a shows that a one-standard-deviation shock to the freight turnover increases SO<sub>2</sub> emission for about three periods before it begins to have a negative effect on SO<sub>2</sub> emission over the long term, except for a brief rise in the 16th period. The impulse response shows that the increase in freight turnover during the initial year increases the SO<sub>2</sub> emission; this suggests it would be worthwhile to more extensively introduce the use of clean energy vehicles in transport companies. Beijing has many preferential policies for EP-type automobiles. Such measure also reduces air pollution over the long term.

SO<sub>2</sub> emission shows a negative response to population size growth in the early stages (Fig. 2b). This reflects that an increase in the urban population causes industrial enterprises

**Table 4** Vector autoregression estimates

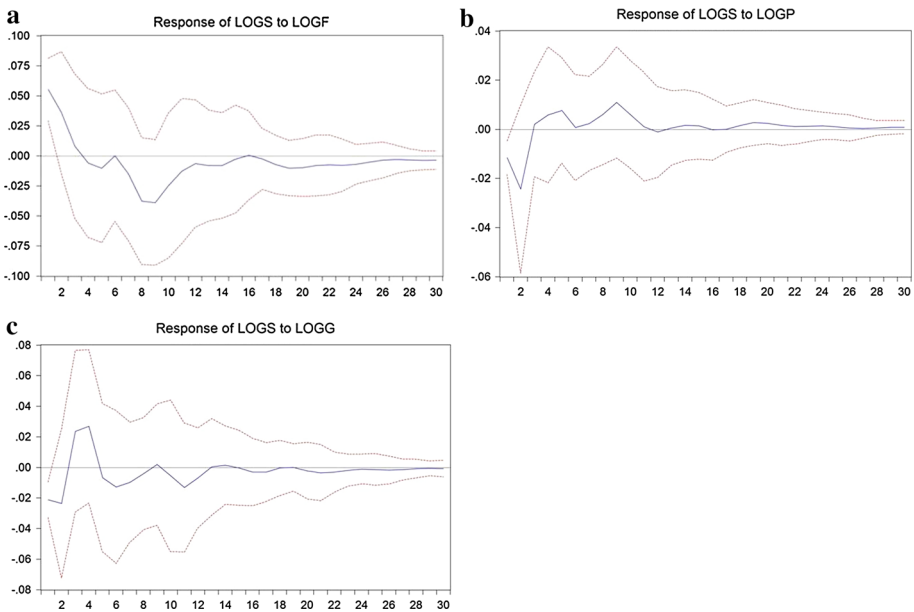
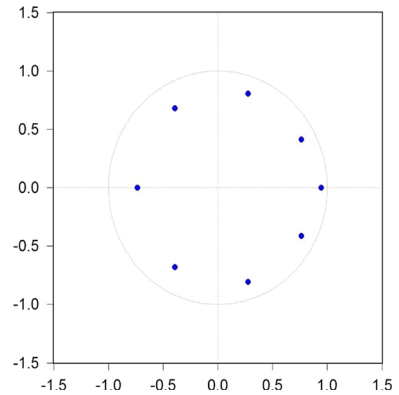
	LOGF	LOGG	LOGP	LOGS
LOGF(−1)	0.022518 (0.36765) [0.06125]	−0.237799 (0.22753) [−1.04512]	−0.134211 (0.03804) [−3.52847]	0.031426 (0.53331) [0.05893]
LOGF(−2)	0.158091 (0.39408) [0.40116]	0.078523 (0.24390) [0.32195]	−0.090442 (0.04077) [−2.21825]	−0.719911 (1.06811) [−0.99944]
LOGG(−1)	1.510769 (0.73631) [2.05180]	0.804059 (0.45570) [1.76446]	−0.047352 (0.07618) [−0.62159]	−1.067508 (1.06811) [−0.99944]
LOGG(−2)	−1.608503 (0.90217) [−1.78293]	0.154985 (0.55834) [0.27758]	0.267032 (0.09334) [2.86092]	1.831392 (1.30869) [1.39941]
LOGP(−1)	0.211466 (3.87788) [0.05453]	0.217734 (2.39998) [0.09072]	0.046357 (0.40120) [0.11554]	−6.519221 (5.62530) [−1.15891]
LOGP(−2)	1.580906 (3.50886) [0.45055]	0.817602 (2.17160) [0.37650]	0.686549 (0.36302) [1.89119]	3.210431 (5.09000) [0.63073]
LOGS(−1)	0.673839 (0.28189) [2.39046]	0.424172 (0.17446) [2.43138]	0.031293 (0.02916) [1.07300]	0.619949 (0.40891) [1.51610]
LOGS(−2)	−0.721982 (0.29780) [−2.42443]	−0.018370 (0.18430) [−0.09933]	0.087531 (0.03081) [2.84102]	−0.239800 (0.43199) [−0.55511]
C	0.638906 (13.0277) [0.04904]	−9.510745 (8.06275) [−1.17959]	2.102589 (1.34784) [1.55997]	35.82966 (18.8982) [1.89593]
$R^2$	0.988999	0.999194	0.999720	0.988520
Adj. $R^2$	0.966998	0.997582	0.999161	0.965561
Sum sq. resids	0.007100	0.002719	7.60E−05	0.014940
SE equation	0.042130	0.026074	0.004359	0.061115
$F$ –statistic	44.95248	619.9629	1786.499	43.05574
Log likelihood	30.38584	36.62359	59.87734	25.55003
AIC	−3.290129	−4.249783	−7.827283	−2.546158
SC	−2.899011	−3.858664	−7.436164	−2.155039
Mean dependent	15.39256	9.251120	7.473740	11.78947
SD dependent	0.231915	0.530301	0.150447	0.329325

Standard errors in () and  $t$  statistics in []

to relocate, reducing the emission of  $\text{SO}_2$  in the metropolitan region over the short term. However, in the long run, population growth is likely to increase air pollution linked to traffic, causing  $\text{SO}_2$  emission to show a positive response over time.



**Fig. 1** VAR roots of characteristic polynomial



**Fig. 2** Responses of the SO<sub>2</sub> emission to influencing factors. **a** Response of LOGS to LOGF. **b** Response of LOGS to LOGP. **c** Response of LOGS to LOG

Figure 2c shows the impulse response function for SO<sub>2</sub> emission related to a one-standard-deviation shock of GDP growth. SO<sub>2</sub> emission fluctuates positively and negatively after this impact, indicating that the effect of increasing Beijing’s GDP on air pollution is not clear.

### 3.5 Variance decomposition

Variance decomposition analyzes the contribution degree of each impact on the endogenous variable, highlighting the importance of different structural shocks. Therefore, variance decomposition can illustrate the relative importance of a given factor in the VAR model. To quantitatively describe the contributions of freight turnover, GDP and

**Table 5** Variance decomposition analysis

Period	SE	LOGF	LOGG	LOGP	LOGS
1	0.061115	82.34859	11.92836	3.536216	2.186834
2	0.078807	70.46897	16.05348	11.65692	1.820639
3	0.082842	64.74967	22.70501	10.61068	1.934644
4	0.087635	58.30472	29.77016	9.933365	1.991746
5	0.088829	58.07134	29.53758	10.42259	1.968482
6	0.089754	56.88119	30.97131	10.21545	1.932048
7	0.091507	57.32958	30.91373	9.895572	1.861120
8	0.099253	63.06811	26.45126	8.786489	1.694135
9	0.107194	67.11203	22.71016	8.578541	1.599269
10	0.110291	68.37115	21.69609	8.408220	1.524538

population size on SO<sub>2</sub> emission, variance decomposition of our VAR model is given in Table 5. Here, the contributions to changes in SO<sub>2</sub> emission standard error are shown for freight turnover, GDP, population, and SO<sub>2</sub> emission.

The initial impact of freight turnover on the forecast error variance of emissions is approximately 82%, which is much higher than any other variable in this system. Although it drops to its lowest contribution on the 7th period, it then continues to rise. GDP shocks ranked second for its relative contribution. This shock accounts for around 12% of the forecast error variance over the short term and 22% over the long term. Population growth explains only a small part of the forecast error variance, accounting for around 8% over the long term. SO<sub>2</sub> emission had little independent impact, with a consistent contribution of about 2%.

## 4 Discussion and conclusions

We examined some possible factors that increase SO<sub>2</sub> emission in Chinese metropolitan regions, using data from Beijing as our test. Beijing has a high requirement for environmental quality, it has little heavy industry enterprises located within the metropolitan region, but a high-level of logistic activities related to goods and services. Therefore, it is representative of other inland cities in China. A VAR model was used explore empirical effects on SO<sub>2</sub> emission linked to various economic factors, covering the period 2000–2014.

First, our model showed that expansion of logistic services has a strong effect on air pollution. Growth in logistic services, especially freight turnover, had an initial positive impact on air pollution, but became negative over the long term. This implies that the effects on air pollution related to future the expansion of logistic services need to be addressed. Preferential policies for clean energy automobiles need to continue to be implemented. However, because serious air pollution can result from increased logistic activities, the Beijing government should adopt appropriate measures to control urban logistics. Such measures will mitigate air pollution becoming more serious during busy economic periods.

The second finding of our model is that population growth had only a small effect on air pollution. This confirms the findings of Zhu and Peng (2012). Our analysis showed that the increase in population only aggravated air pollution directly after the initial impact, with

time it became a positive effect. This supports the government policy to shift industries that contribute metropolitan region to reduce urban air pollution. However, the rapid growth in transportation and private vehicles related to population growth still affects air quality. Thus, it is reasonable to continue to control population growth in Beijing.

Finally, growth in GDP in Beijing caused both positive and negative fluctuations in air pollution. However, Yu et al. (2015) pointed out that GDP growth rate has a great influence on the carbon emissions in Beijing. Our inconclusive trend could reflect that a positive shock to the economy would raise oil prices, increasing costs of rail transport. At the same time, growth in GDP may increase logistic services and transportation, resulting in a positive response. Hence, the influence of GDP on air pollution is not clear. However, according to the Variance decomposition analysis, GDP still makes a contribution to air pollution.

Our study shows that growth of logistics services has a big effect on air pollution. Currently, the trucks used for most transportation in China use diesel fuel. Although heavy-duty diesel vehicles only account for about 4% of the motor vehicle inventory, their emissions of nitrogen oxides and particulate matter account for more than 50 and 90% of the total emissions of motor vehicles, respectively. Thus, municipal governments need to make a reasonable future plan for transportation, which mitigates air pollution. Given that the population of China exceeded 1.36 billion in 2015 and that urban populations account for 54.7% of this population, it is clear that China needs to set policies to reduce population size. In particular, attention should be given to distributing the population to least impact the environment.

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#### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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