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Does the joint prevention and control regulation improve the air quality? A quasi-experiment in the Beijing economic belt during the COVID-19 pandemic

Chenlu Tao\textsuperscript{a,*}, Kent Wheiler\textsuperscript{b}, Chang Yu\textsuperscript{a}, Baodong Cheng\textsuperscript{a,*}, Gang Diao\textsuperscript{a,*}

\textsuperscript{a} School of Economics and Management, Beijing Forestry University, Beijing 100083, China
\textsuperscript{b} School of Environment and Forest Science, University of Washington, Seattle, WA 98195, USA

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\textbf{A B S T R A C T}

This study aims to clarify the correlation between air pollution of cities in Beijing Economic Belt from a time-varying perspective and estimate effects of joint prevention and control regulation of air pollution. The COVID-19 pandemic provides a unique opportunity. Based on daily data of air quality, we used TVP-VAR model and utilize the pandemic as a quasi-experiment to assess the policies. The results show air pollution in surrounding cities does influence Beijing’s air quality, but the relationship has been weakening year by year, mainly due to industrial adjustment which have achieved progress on alleviating the path of air pollution. Therefore, it is necessary to implement joint regulation in areas with serious pollution. Specifically, the relationship between the air quality of Beijing and Zhangjiakou, Chengde, Tianjin decreased as the pandemic became worse. In contrast, there was no significant decline in Langfang and Baoding. So unlike Baoding and Langfang, industrial production increased relationships between air quality of Beijing and the other three cities, which highlights the validity of restrictions. However, restrictions implemented on Baoding and Langfang affect economic development but have little effect on Beijing’s air governance. Therefore, joint regulation contributes to realizing sustainable cities, but more targeted policies should be formulated.

1. Introduction

The Beijing-Tianjin-Hebei region is one of the most severely polluted areas in China (Wang et al., 2014; Wang, Li, Qiao & Lu, 2019; Yan et al., 2018). Air pollution has become a major threat to human health (Halim, Latif & Mohamed, 2020; Zou et al., 2019) and an important problem for facilitating sustainable development (Mao, Wang & Jiao, 2021). Concurrent with the considerable economic development of the past few decades, Beijing and its surroundings have suffered severe air pollution, causing substantial loss (Gao et al., 2015; Guo et al., 2010; Xin, Shao & Wang, 2021; Yin, Pizzol & Xu, 2017; Zou et al., 2019). As Guo et al. (2018) pointed out if the PM2.5 concentration fell by 11.27%, the total economic benefit from health impacts could achieve 3.9 billion USD in the Beijing-Tianjin-Hebei region. The readily disperse of air pollution (Henderson, 1977; Zhang et al., 2019a) determines that the air quality control depends not only on the emission reduction in a city but also on the pollutant control from the surrounding areas (Qin et al., 2015; Zheng et al., 2015; Wang et al., 2019). Therefore, it is difficult to fundamentally solve air pollution by only restricting production and living activities in one city (Song, Li, Yang & Xia, 2020a; Zhang, Liu & He, 2016). The joint prevention and control regulation is a series of policies relying on organizational resources to break down the administrative boundaries, and ultimately achieving shared governance results (Song et al., 2020a). Optimizing regional industrial layout and limiting production and emission are two important governance measures (General Office of the State Council of China, 2010). The State Council of the People’s Republic of China has formulated a series of measures and regulations for the improvement of air quality (Jin, Andersson & Zhang, 2016; Li, Qiao, Zhu, Shi & Wang, 2017; Shi, Wang, Chen & Huisingh, 2016) in regions with serious air pollution (Song, Zhang & Zhang, 2020b) and showed a significant downward trend of the concentration of air pollutants (Zhao et al., 2021; Zang, Nakatani, Man & Moriguchi, 2019b). Beijing-Tianjin-Hebei region has also carried out a series of industrial layout adjustments from 2014 to reduce the spread of air pollution by adjusting the industrial layout (Geng, Wang, Ettema & Anderson, 2020; Ministry of Natural Resources of China, 2014; Shi et al., 2018).
The COVID-19 pandemic provides an opportunity to analyze the effects of joint prevention and control regulation since it has reduced human activities (Sathe, Gupta & Bawase, 2021). Before the outbreak of the COVID-19, the relationship between cities was affected by both human activities and natural geographical conditions. The coronavirus disease had massive impacts on society and the economy across large parts of China, including the Beijing-Tianjin-Hebei region (Chen et al., 2020; Leung, Wu, Liu & Leung, 2020; Zhang and Ma, 2020; Han et al., 2021a). Covid-related restrictions, both mandated and voluntary, have in effect created a ‘natural experiment’. During the outbreak, Beijing was influenced by various control policies (Wang, Chen, Zhu, Wang & Zhang, 2020b, 2020a). In late January, public transport and most enterprises were suspended, and several areas were even locked down (Tian et al., 2020). After February 10, the government allowed some industries to get back to work, but the resumption process was complicated. Beijing’s GDP decreased by 6.6% in the first quarter of 2020 (Beijing Municipal Bureau of Statistics, 2020). On June 12, the coronavirus was detected again in salmon in the Beijing Xinfadi Market (Han et al., 2020). The enterprises were affected again. Beijing finally contained the second pandemic by partial quarantine (Brimblecombe and Lai, 2021b). The enterprises were affected once more. Beijing finally contained the second pandemic by partial quarantine (Brimblecombe and Lai, 2021b). Before the outbreak of the COVID-19 pandemic, the factors affecting the air quality transmission between cities were impacted by social economy and industrial production for specific periods. Therefore, we could conduct comparative research based on the assumption that the COVID-19 pandemic created a quasi-experiment.

2. Methodology and data

2.1. Methodology

The COVID-19 pandemic provides an opportunity to analyze the effects for sustainable cities of air quality joint prevention and control policies in the Beijing Economic Belt since it reduced human activities, like a ‘natural experiment’. The pandemic in 2020 significantly impacted the social economy and industrial production for specific periods. Therefore, we could conduct comparative research based on the assumption that the COVID-19 pandemic created a quasi-experiment.

2.1.1. TVP-VAR model

TVP-VAR model (Brommelen, 2005), which breaks the assumption that the estimated coefficients of the traditional VAR model are constant and allows for dynamic interaction between variables more accurately, is as follows:

\[
y_t = X_t β_t + Σ_t ε_t, \ ε_t \sim N(0, I_n), t = s + 1, \ldots, n, \text{ and, } Σ_t = \begin{bmatrix} ε_{1t} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & σ_{nt} \end{bmatrix} \tag{1}\n\]

Among them, \(X_t = I_n \otimes (y_{t-1}, \ldots, y_{t-s})\), and \(\otimes\) means Kronecker product, the coefficients \(β_t\), parameter \(A_t\) and matrix \(Σ_t\) all change with time. This paper involves a total of \(m\) variables. Let \(α_t\) denote the stacked vector of lower triangular elements in matrix \(A_t\), and \(H\) be the logarithmetic random volatility matrix. Suppose \(h_t = \ln σ_{tt}\), and for all \(j = 1, \ldots, m, t = s + 1, \ldots, n\) they are first-order random walk processes, which is

\[
\begin{align*}
β_{t+1} & = β_t + μ_β, \\
α_{t+1} & = α_t + μ_α, \\
h_{t+1} & = h_t + μ_h.
\end{align*}
\]

We assume that \(ε_t, μ_β, μ_α, μ_h\) obey:

\[
\begin{bmatrix} ε_t \\ μ_β \\ μ_α \\ μ_h \end{bmatrix} \sim N(0, V), \text{ there into, } V = \begin{bmatrix} I_000 \\ Σ_β00 \\ 000Σ_α \\ 0000Σ_h \end{bmatrix}, \text{ where } β_{t+1} \sim N(μ_β, Σ_β), α_{t+1} \sim N(μ_α, Σ_α), h_{t+1} \sim N(μ_h, Σ_h).
\]

The assumption indicates that the impacts of time-varying parameters are uncorrelated, and that \(Σ_β, Σ_α, Σ_h\) are all diagonal matrices. The estimation of the model in this paper is done by the Markov Chain Monte Carlo method (MCMC) (Nakajima, Kasuya & Watanabe, 2011).

TVP-VAR model can achieve the goal of this research. In recent years, the joint prevention and control policies of the air quality have led to significant adjustments in the industrial layout and industrial policies in 2020, which significantly reduced the societal impact on the air pollutant transfer between cities.

This research aims to clarify the correlation between the air quality of cities in the Beijing Economic Belt from a time-varying perspective, estimate the effects of the joint prevention and control regulation of air pollution for sustainable development, and uncover possible improvements. To this end, we chose the time-varying parameter autoregressive (TVP-VAR) model to study the air quality transmission between cities around Beijing from a time-varying perspective based on the daily air quality data from 2018 to 2020. In order to assess the rationality of the current industrial layout in the Beijing Economic Belt, we used the two-way analysis of variance (Two-way ANOVA) to compare the differences in the impulse responses in 2020 and 2018–19. Then, since the policy response to the COVID-19 pandemic in the Beijing-Tianjin-Hebei region was synchronized, we used the autoregressive distributed lag (ARDL) model to measure the impact of the pandemic on the relationship between the air quality of cities. Recently, researchers were also concerned about the relationship between air quality of cities, but most of them analyzed annually or quarterly (Wang et al., 2019; Wang, Wie, Lei, Wang & Wu, 2017; Zheng et al., 2017; Wang, Li, Wu, Gao, & Li, 2008; Meng et al., 2006). However, air quality, especially PM2.5, has a small particle size, which can diffuse fast and far away (Wang et al., 2017), so research with high-frequency data can consider its flow process. Baoding, Chengde, Langfang, Zhangjiakou, and Tianjin are 140 km, 172 km, 40 km, 164 km, and 127.4 km from Beijing. The average wind speed in Beijing-Tianjin-Hebei is around 2.07 m/s (Chen et al., 2020; Shi, Gong & Hu, 2019). Therefore, we chose daily data for analysis since it is most suitable. Existing studies are in the regular work period, and there are interferences of emissions from suburban enterprises or mines, tourist attractions, and cross-regional traffic, which may affect the accuracy of the results. During the COVID-19 pandemic, the factors affecting the air quality transmission between cities were driven more by nature. Therefore, we could conduct comparative research based on the assumption that the pandemic provided a quasi-experiment to estimate the outcome of air quality policies, which created a control group close to the natural state for the research. These could also be general lessons that other countries might learn from existing evidence in the Beijing Economic Belt regarding air governance.
the Beijing-Tianjin-Hebei region. The relationship between air quality of cities is obviously varying as time goes on. Traditional quantitative analysis methods such as VAR and SVAR are suitable for the study of maintaining a constant relationship between variables. However, during the COVID-19 pandemic, which has both prominent time-varying characteristics, traditional methods are likely to miss critical time-varying information. In comparison, the TVP-VAR model can capture the relationship and characteristics of variables in different contexts (Wu & Fu, 2014) and avoid the loss of observations (Antonakakis, Gabauer & Gupta, 2019; Baek, 2015; Balli, Çatık & Nugent, 2021; Gabauer & Gupta, 2018). Moreover, this model does not have the same variance limitations as the VAR model, which is practical in research about air quality. The lag effect of the explanatory variables can also be put into the model, and then the predictive ability (Wang, 2021; Fan & Matlab R2017b to display the results.

2.1.2. ARDL model

The ARDL model can include the inertia of the variables to improve the predictive ability (Wang, 2021; Fan & Wei, 2020; Baek, 2015), which is practical in research about air quality. The lag effect of the explanatory variables can also be put into the model, and then the problem can be considered comprehensively (Wang, 2021; Fan & Wei, 2020; Baek, 2015). The sample size we used in this manuscript is only 275–365, and the ARDL model can achieve comprehensive extraction of variable characteristics with limited data. In addition, the ARDL can avoid endogenous problems (Fang, Wu, & Zhang, 2017; Pesaran et al., 2001). Therefore, to measure the impact of the COVID-19 pandemic on the transmission of air quality between cities from a time-varying perspective, we used the ARDL model (Nkoro & Uko, 2016; Sari, Ewing & Soytas, 2008) and we estimated separately to retain more information. The models are as follows:

\[ BAD_t = \beta_0 + \sum_{i=1}^{q} \beta_i BAD_{t-i} + \sum_{i=1}^{s} \beta_i covid_{t-i} + \epsilon_t \]  
\[ CHD_t = \beta_0 + \sum_{i=1}^{q} \beta_i CHD_{t-i} + \sum_{i=1}^{s} \beta_i covid_{t-i} + \epsilon_t \]  
\[ LAF_t = \beta_0 + \sum_{i=1}^{q} \beta_i LAF_{t-i} + \sum_{i=1}^{s} \beta_i covid_{t-i} + \epsilon_t \]  
\[ ZJK_t = \beta_0 + \sum_{i=1}^{q} \beta_i ZJK_{t-i} + \sum_{i=1}^{s} \beta_i covid_{t-i} + \epsilon_t \]  
\[ TJJ_t = \beta_0 + \sum_{i=1}^{q} \beta_i TJJ_{t-i} + \sum_{i=1}^{s} \beta_i covid_{t-i} + \epsilon_t \]  

where BAD, CHD, LAF, ZJK, and TJJ represents the impulse responses of Beijing’s air quality to Baoding’s, Chengde’s, Langfang’s, Zhangjiakou’s, and Tianjin’s air quality shock, respectively. We used Eviews10 to estimate the models.

2.2. Data

The phase of the pandemic can be judged based on changes in the number of confirmed COVID-19 cases. Moreover, the joint prevention and control of the pandemic in the Beijing-Tianjin-Hebei region made the pandemic response policy consistent. Therefore, this paper selected the number of newly confirmed COVID-19 cases in Beijing from January to September 2020 to represent the COVID-19 pandemic (covid). The data was retrieved from the ‘Daily Epidemic Bulletin’ of the Beijing Municipal Health Commission (http://wjj.beijing.gov.cn/)

Our research used PM2.5 to represent air quality. PM2.5 is one of the critical standards for measuring air quality (Pope, Dockery, & Schwartz, 1995; Chowdhury, Pozzer, Dey, Klingmueller & Lelieveld, 2020), and the Beijing-Tianjin-Hebei region is an area with serious PM2.5. Therefore, we extracted the hourly data of PM2.5 from 2018 to 2020 in Beijing (pek) and surrounding cities, namely Baoding (bad), Chengde (chd), Langfang (laf), Zhangjiakou (zjk), Tianjin(tjj), and then calculated the daily average with the aggregate function of R. Then we analyzed the relationship between the air quality of Beijing and Baoding, Chengde, Langfang, Zhangjiakou, Tianjin. The data came from China Environmental Monitoring Center (http://www.cnemc.cn/).

In addition, this paper used Multiple Imputation, based on five replications and a chained equation approach method in the R multiple imputation procedure, to account for missing data (Pil, Wang, Chen, Zheng & Hu, 2021; Su, Gelman, Hill & Yajima, 2011). Since the air quality data used in this article was daily data from January 1, 2018, to September 30, 2020, the seasonality and periodicity of the data should be considered. Therefore, we adjusted the seasonally by constructing monthly dummy variables and taking residuals in 2018, 2019, and 2020. Descriptive statistics of the data can be seen in Appendix A Table A1.

3. Dynamic transmission of air quality in Beijing economic belt

3.1. Unit root test

We tested the stationarity properties of the series using the augmented Dickey–Fuller (ADF) test. The maximum lag order was 17 in 2018 and 2019, 15 in 2020 (Schwert, 2002). The seasonally adjusted sequences of six variables, namely air quality in Baoding, Chengde, Langfang, Zhangjiakou, Tianjin, and Beijing, were stationarity and met the requirements of the TVP-VAR model.

Table 1

| Time | Parameter | Mean | Stdev. | 95% percent interval | CD | Inefficiency |
|------|-----------|------|--------|----------------------|----|--------------|
| 2018 | S1_2      | 0.0219 | 0.0023 | [0.0178, 0.0269]     | 0.591 | 18.16        |
|     | S2_2      | 0.0227 | 0.0025 | [0.0186, 0.0281]     | 0.963 | 15.42        |
|     | S3_1      | 0.0494 | 0.0098 | [0.0343, 0.0718]     | 0.990 | 47.15        |
|     | S4_2      | 0.0594 | 0.0136 | [0.0382, 0.0912]     | 0.687 | 82.33        |
|     | S5_1      | 0.3160 | 0.0633 | [0.2117, 0.4601]     | 0.582 | 73.74        |
|     | S6_2      | 0.5049 | 0.1052 | [0.3288, 0.7363]     | 0.569 | 99.48        |
| 2019 | S1_2      | 0.0224 | 0.0024 | [0.0181, 0.0277]     | 0.134 | 15.27        |
|     | S2_2      | 0.0225 | 0.0025 | [0.0182, 0.0278]     | 0.172 | 17.54        |
|     | S3_1      | 0.0630 | 0.0129 | [0.0414, 0.0958]     | 0.729 | 60.85        |
|     | S4_2      | 0.0483 | 0.0091 | [0.0332, 0.0689]     | 0.914 | 50.35        |
|     | S5_1      | 0.3700 | 0.0673 | [0.2444, 0.5088]     | 0.899 | 42.44        |
|     | S6_2      | 0.5163 | 0.1060 | [0.3035, 0.7406]     | 0.164 | 103.99       |
| 2020 | S1_2      | 0.0223 | 0.0024 | [0.0181, 0.0273]     | 0.910 | 12.21        |
|     | S2_2      | 0.0225 | 0.0025 | [0.0183, 0.0279]     | 0.488 | 6.23         |
|     | S3_1      | 0.0632 | 0.0169 | [0.0383, 0.1022]     | 0.713 | 55.98        |
|     | S4_2      | 0.0601 | 0.0147 | [0.0384, 0.0987]     | 0.540 | 57.36        |
|     | S5_1      | 0.3152 | 0.0704 | [0.1968, 0.4764]     | 0.326 | 55.14        |
|     | S6_2      | 0.3512 | 0.0885 | [0.2084, 0.5439]     | 0.332 | 69.23        |
3.2. Estimation results by MCMC

The Bayesian Information Criterion (BIC) and Hannan-quinn Criterion (HQ) provides a consistent estimate of the correct lag order (Lütkepohl, 2005), so we set the lag order for estimation as 1 in 2018 and 2019, and 2 in 2020. We referred to the method of Nakajima et al. (2011) to set the initial values: $\mu_0 = \mu_\alpha = \mu_\epsilon = 0$, $\Sigma_0 = \Sigma_\alpha = 10I$, $\Sigma_\epsilon = 100I$, $(\Sigma_\alpha)_{ij}^{-1} \sim \gamma(40, 0.02)$, $(\Sigma_\epsilon)_{ij}^{-1} \sim \gamma(4, 0.02)$, $(\Sigma_\epsilon)_{ij}^{-1} \sim \gamma(4, 0.02)$. Then we used OxMetrics to execute the MCMC algorithm for 10,000 samplings and discarded the first 1000 samplings, thereby obtaining valid samples for model posterior estimation. Table 1 showed the probability of Geweke Convergence Diagnostics value (CD) was greater than 5%, indicating that the pre-burning period was sufficient to make the Markov chain tend to be concentrated. The invalid factors (Inefficiency) were all below 150, indicating an efficient sampling for the parameters and the effective model estimation. So the results would be robust (Zheng & Ding, 2019).

3.3. Time-Varying impulse analysis

Fig. 1 shows the dynamic impulse responses, which are obtained by considering one standard deviation shocks, from TVP-VAR model. We just took the impulse responses of equal intervals for a 1-day horizon, a 2-day horizon, and a 7-day horizon, which represented the short-term, mid-term, and long-term, respectively, as an example. Generally speaking, Beijing’s air quality had positive impulse responses to the air quality in Baoding, and the value was relatively large with the maximum response value of 18.86 in the short term (Fig. 1(a)).

![Fig. 1. Impulse responses of air quality in Beijing to surrounding cities in 2018, 2019, and 2020.](image-url)
It shows that Baoding is one of the main cities that affect Beijing’s air quality. Furthermore, it also illustrates that air quality in one city is influenced by the air quality of nearby areas (Qin et al., 2015; Zheng et al., 2015; Wang et al., 2019). From a longitudinal comparison, the impulse response decreased from 2018 to 2019. It is mainly owing to Baoding’s industrial adjustment. In recent years, Baoding has stepped up industrial restructuring. The Government promotes eliminating backward high-energy and high-emission equipment by administrative means (Zhang et al., 2019b). In accordance with the Baoding municipal government’s guidance on controlling the low-carbon pilot city, in the future, the city will comprehensively upgrade to the modern financial industry and enhance the financial industry’s supporting capacity and service functions for economic development. Therefore, Baoding’s industrial structure, which is dominated by the high-energy and energy-intensive heavy chemical industry, changes slightly (Zhang et al., 2019b). With the industrial adjustment, the relationship between air quality in the two cities decreased. The impulse response in 2020 was obviously lower than that in 2018, but it was not much different from that in 2019. The average impulse response of one-day horizon was 11.89 in 2020 and 12.55 in 2019, which is much lower than 2018 (17.88). It shows that the pandemic’s occurrence did not seriously influence the relationship between air quality in Baoding and Beijing. In other words, the production restriction policy, which was always used in joint prevention and control policies, may no longer necessarily apply to Baoding. The trends of the impulse response in 2018, 2019, and 2020 were similar, which all went up in the second quarter and became low in winter. It demonstrates that the relationship between the air quality of Baoding and Beijing was stronger in summer than in winter.

The impulse responses of Beijing’s air quality to the air quality in Chengde were positive, with a maximum value of 7.50 (Fig. 1(b)). It illustrates that air pollution in Chengde would cause subsequent deterioration of air quality in Beijing. According to the results, the impulse response value in 2020, with a maximum of only 3.98, was much lower than that in 2018 and 2019. It indicates that compared with 2018 and 2019, the impact of Chengde’s air quality on Beijing became lower in 2020. In other words, reducing human activities will weaken the correlation between the air quality in these two cities, and limiting production might be useful to control air quality. From 2015, Chengde City began to shift its industrial development focus to green industries, and the proportion of the added value of the tertiary industry has increased year by year (Chengde Municipal Government, 2019). From 2017 to 2020, the number of industrial companies in Chengde has decreased by 24.18% (Ministry of Ecology and Environmental Protection of China (MEPC) 2017; Ministry of Ecology and Environmental Protection of China MEPC, 2020). The decline of the impulse response from 2018 to 2020 also proved that Chengde’s industrial adjustment had achieved progress on alleviating the path of air pollution and sustainable development.

By contrast, for Langfang, the impulse response value in 2020 was higher than that in 2018 and 2019 (Fig. 1(c)), indicating the impact of Langfang’s air quality on Beijing became stronger in 2020 than in 2018 and 2019. The shutdown did not reduce the impact of Langfang air pollution on Beijing’s air quality. Moreover, the impulse response in 2019 was significantly lower than in 2018, indicating that the adjustment of the industrial layout was effective, and the industrial layout was becoming reasonable. Meanwhile, the impulse response did not decrease when production was reduced, indicating Langfang could assume part of Beijing’s industrial functions but had a small impact on Beijing’s air quality. The impulse responses of Beijing’s air quality to Langfang were all positive, with a maximum value of 6.76. It illustrates that if the air quality in Langfang became worse, the air quality in Beijing would also become poorer. The trends of the impulse response in three years were similar, which all increased in the second quarter and declined in winter. It means the impact of Langfang’s air quality on Beijing is more substantial in summer than in winter. If paying more attention to 2020, the impulse responses of Beijing’s air quality to Langfang’s shock were stable. As people returned to work, the relationship between air quality in Beijing and Langfang did not change seriously.

In Fig. 1(d), the impulse response has been declining, indicating that Zhangjiakou’s industrial layout was constantly adjusting from 2018 to 2020. The impulse response in 2020 was significantly lower than in 2018 and 2019, the same as the situation with Chengde, indicating the suspension of production indeed could reduce the impact of air pollution in Zhangjiakou on the air in Beijing. The restrictions on production and emission in Zhangjiakou were reasonable. Furthermore, the impulse responses of Beijing’s air quality to Zhangjiakou were positive in 2018 and 2019, while increasingly negative from May 2020. It may be caused by seasonal factors. Surface winds over the Beijing-Tianjin-Hebei region are dominated by the southerly wind in summer, with an average wind speed of 1.88 m/s (Chen et al., 2020b; Liao et al., 2014; Shi et al., 2019). Thus, Zhangjiakou’s air quality was possibly getting worse, but Beijing’s was improving.

For Tianjin, the impulse response in 2020 was also obviously lower than that in 2018 and 2019 (Fig. 1(e)). The impact of Tianjin’s air quality on Beijing was smaller in 2020 than before. It means that reducing human activities reduces the impact of Tianjin’s air quality on Beijing. Therefore, although the number of industrial companies in Tianjin decreased by 13.63% from 2013 to 2020 (Ministry of Ecology and Environmental Protection of China (MEPC) 2013; Ministry of Ecology and Environmental Protection of China MEPC, 2020), Tianjin’s industrial layout should still be adjusted, and enterprises with severe air pollution should be moved out. Beijing’s air quality had positive impulse responses to the air quality in Tianjin, with a maximum response of only 3.11. The trends of the impulse response in 2018, 2019, and 2020 were similar, which all went up in the second quarter and became low in winter. It demonstrates that the relationship between the air quality of Tianjin and Beijing was stronger in summer than in winter. Specifically, the impulse responses of Beijing’s air quality to Tianjin went up before June in 2020 and then decreased. With the economic recovery, the dynamic transmissions between Beijing’s and Tianjin’s air quality strengthened. While the arrival of the second outbreak, the relationship declined again.

In terms of the impulse response of different time points, the responses at various points were nearly consistent (Fig. 1(a-e)). Comparing with the impulse responses of a 2-day horizon and a 7-day horizon, most values had the same tendency as that of a 1-day horizon. And the bigger the horizon is, the smaller the response is. Almost all impulse responses converge near 0 after 7-day horizon. Therefore, the air quality transmissions between Beijing and the cities around were mainly short-term.

4. The assessment of the joint prevention and control regulation of air pollution

4.1. The rationality of the restriction policy and the industrial layout

Based on Section 3, we paid attention to the months when the natural realization effect was most prominent in 2020 and compared the impulse responses with that in 2018 and 2019 by Two-way ANOVA. Since February, March, June, and July 2020 were the most severe months of the pandemic, this “quasi-experiment” had the most prominent effect at these times. Therefore, we chose the mean impulse responses in these months to analyze (Fig. 2(a-e)).

According to Fig. 2(a), the impulse responses of Beijing’s air quality to Tianjin’s shock in February, March, June, and July of 2020 were lower than that of 2018 and 2019. Take February as an example. The average impulse response was 2.18 in February 2018 and 1.40 in February 2019, while 0.71 in February 2020. It shows that if the impact of human activities were excluded, the impact of Tianjin’s air quality on Beijing would be reduced. Therefore, Tianjin’s industrial layout adjustment has not yet reached the ideal state. Therefore, the related industrial enterprises should be transferred and the restriction of work would be still useful.
June, and July 2020, the impact of Baoding stopped production and many people worked from home in February, it was only 4680 thousand, a year-on-year decrease of nearly 50% compared to 7938 thousand in 2019. Moreover, from June to July 2020, passenger flow of the Beijing Subway was as low as 1213 thousand, months of 2018. During February and March of 2020, the average daily production in Zhaobou was higher than that in 2019 and even higher than in several

Therefore, Zhangjiakou’s industrial layout adjustment has not yet reached the ideal state, and related industrial enterprises in Zhangjiakou also should be relocated. The restriction of production was essential in Zhaobou. In addition, the average value of the impulse response of Beijing’s air quality to Zhaobou’s shock was negative in June and July 2020, but this might be due to seasonal factors. In summer, the Beijing-Tianjin-Hebei climate is dominated by southeast winds, and Zhaobou is downstream. Therefore, Zhaobou’s air pollution was serious, while Beijing’s air quality had a short-term phenomenon of improvement at that time.

The average impulse responses of Beijing’s air quality to Chengde’s shocks in March, June, and July 2020 were lower than that in 2019 (Fig. 2(c)). For example, the average impulse response was 3.75 in June 2018 and 3.46 in June 2019, while 2.72 in June 2020. The Spring Festival holiday results in well-documented impacts on air pollution (P. Brimblecombe & Lai, 2020b; Lai & Brimblecombe, 2017; Silver et al., 2020; Yang, Fan & Zhao, 2020) and may bring disturbances to the research results. Therefore, although there was no significant decline in February, we still believed that human activities increased the impact of Chengde’s air quality on Beijing owing to the results in the other three months. Therefore, the adjustment of Chengde’s industrial layout has not reached its optimal state. Chengde should assume the function of ecological conservation and reduce industrial production.

In Fig. 2(d-e), the mean impulse responses of Beijing’s air quality to Baoding’s and Langfang’s shock in February, March, June, and July 2020 were higher than that in 2019 and even higher than in several months of 2018. During February and March of 2020, the average daily passenger flow of the Beijing Subway was as low as 1213 thousand, compared to 7938 thousand in 2019. Moreover, from June to July 2020, it was only 4680 thousand, a year-on-year decrease of nearly 50% (Beijing Subway, 2021). It shows that although most of the industries stopped production and many people worked from home in February, March, June, and July 2020, the impact of Baoding’s and Langfang’s air quality on Beijing’s did not decline. It illustrates that in natural

4.2. The impact of the pandemic on the impulse response

We then used the ARDL model to estimate the impact of the pandemic on the responses of Beijing’s air quality to the air quality of the surrounding cities. Since the policy response to the COVID-19 pandemic in the Beijing-Tianjin-Hebei region was synchronized, we used the number of confirmed COVID-19 cases in Beijing to represent the pandemic. According to the ADF test, the six variables are all the I(1) process, which meet the data requirements of the ARDL model. Then we performed a cointegration test, and the results show that data had cointegration relationships. Third, we used Eviews10 to run models. Due to HQ Criteria, the lag lengths p in Model 2–6 were all 2 and the lag lengths q were all 0. In summary, we decided to do ARDL (2, 0) in all five models.

In terms of the estimation results for Model 5 (Table 2), the covid had a negative impact on the responses of Beijing’s air quality to Zhaobou’s air quality shock (−0.00007) at a significance level of 1%, which indicated that the COVID-19 pandemic could effectively improve the influences of Zhaobou’s air quality to Beijing. The regression results for Model 6 also show a negative impact (−0.00009, Table 2), which means the pandemic could significantly decrease the relationship between air quality in Tianjin and Beijing. As for the results for Model 2, the covid negatively impacted the responses of Beijing’s air quality to Chengde’s shock (−0.00016, Table 2). Therefore, human activities would promote the impact of cities around Beijing on Beijing’s air quality. It further proved that the production restriction measures used in joint prevention and control policies were applicable in Zhaobou, Tianjin, and Chengde. In the next step of industrial adjustment, the heavily polluting enterprises in these cities should be relocated.

However, the regression results for Model 2 show the covid had a negative impact on the responses of Beijing’s air quality to Baoding’s air quality shock (−0.00009, Table 2), but it was not significant. Therefore, the pandemic did not significantly change the air quality transmissions.
between Baoding and Beijing. As for the results of Model 4, the *covid* had a positive impact on the responses of Beijing’s air quality to Langfang’s shock (0.000017, Table 2). When there was only natural influence, the impact of Langfang’s air quality on Beijing’s was even larger than that during regular production, indicating that even if the government continued to reduce industry in Langfang, it would be difficult to get the effect of improving Beijing’s air quality in line with expectations. Therefore, the limitation of production and emission in Baoding and Langfang should be in line with local circumstances, considering the economic benefit. Together with the results of Section 4.1, it is concluded that Baoding and Langfang perhaps could take over some industrial enterprises and undertake industrial production functions considering Beijing’s air governance.

5. Discussions

We found that the air quality in Beijing can be seriously affected by the pollutant emissions from the surrounding areas. It is consistent with the conclusion of (Meng et al., 2006; Qin et al., 2015; Zheng et al., 2015). We also found that the relationship of air quality keeps weakening, mainly thanks to joint prevention and control policies, which is similar to the conclusion of Wang et al. (2019). As Beijing removed part of its non-capital functions and other regions also relocated some enterprises, the industrial layout of the Beijing-Tianjin-Hebei has gradually become more reasonable. The joint prevention and control regulation has achieved progress on alleviating the path of air pollution and sustainable development. These could also be general lessons that other countries might learn from existing evidence in the Beijing Economic Belt in terms of air governance. However, there are still problems in the industrial layout of Zhangjiakou and Chengde. According to the "Thirteenth Five-Year Plan for Ecological Environment Protection in Hebei Province", Zhangjiakou and Chengde should assume the function of ecological conservation and reduce the impact of air pollution on Beijing. The goal has not yet been fully achieved.

Except for Baoding and Langfang, industrial production increased the air pollution relationship between Beijing and the other three cities. It is quite different from the conclusion of Wang et al. (2008), which may be due to the difference in the research subjects. Our finding supports the validity of the restrictions on production and emission that have been implemented in recent years. Every heating season and for some special days, the authorities implemented limiting production and emission to alleviate air pollution in Beijing and its surroundings. However, according to this research, the policies should not be "one size fits all" and should be spatially heterogeneous.

6. Conclusions

Based on the opportunity provided by the pandemic, this research aims to clarify the dynamic air pollution correlation between cities in Beijing Economic Belt, estimate the effects for sustainable cities of the joint prevention and control regulation of air pollution, and uncover possible improvement. The research results show that: First, air pollution in surrounding cities does influence Beijing’s air quality, but the relationship has been weakening year by year, mainly due to the industrial adjustment of joint prevention and control policies. However, there are still problems in the industrial layout of Zhangjiakou and Chengde, and further industrial adjustments were still needed to achieve sustainability. While considering the months when the natural

### Table 2

The ARDL model estimation results.

| Year | Variable | N  | Mean | SD  | Min | Max |
|------|----------|----|------|-----|-----|-----|
| 2018 | bad      | 365 | 66.871 | 47.794 | 12.792 | 356.500 |
|      | chd      | 365 | 32.222 | 23.726 | 7.792 | 161.750 |
|      | laf      | 365 | 51.678 | 37.630 | 10.417 | 284.780 |
|      | zjk      | 365 | 30.840 | 22.048 | 8.323 | 189.833 |
|      | tij      | 365 | 51.262 | 37.413 | 7.542 | 276.417 |
|      | pek      | 365 | 50.825 | 42.602 | 4.417 | 240.375 |
| 2019 | bad      | 365 | 58.296 | 51.649 | 11.333 | 400.833 |
|      | chd      | 365 | 29.515 | 19.898 | 6.833 | 138.250 |
|      | laf      | 365 | 46.104 | 38.236 | 6.458 | 317.125 |
|      | zjk      | 365 | 25.904 | 37.413 | 7.542 | 276.417 |
|      | tij      | 365 | 51.387 | 39.604 | 7.333 | 247.458 |
|      | pek      | 365 | 42.147 | 32.385 | 4.417 | 240.375 |
| 2020 | new      | 274 | 35.54 | 7.256 | 0.000 | 36.000 |
|      | bad      | 274 | 47.412 | 48.690 | 8.833 | 377.458 |
|      | chd      | 274 | 42.450 | 20.187 | 8.125 | 165.875 |
|      | laf      | 274 | 40.774 | 36.151 | 8.167 | 247.375 |
|      | zjk      | 274 | 23.727 | 15.551 | 8.167 | 95.833 |
|      | tij      | 274 | 47.114 | 38.544 | 7.333 | 240.708 |
|      | pek      | 274 | 38.904 | 32.985 | 4.000 | 206.375 |

Note: standard error values are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.
realization effect was most prominent in 2020, there was a significant decline in the mean air quality compared with that in 2018 and 2019. It shows that industrial production still would increase the relationship between the air quality of these cities with Beijing. Thus, the industrial adjustment should continue. Second, according to the quasi-experiment, the relationship between air quality of Beijing and Zhangjiakou, Chengde, and Tianjin weakened during the pandemic compared with the previous two years, while there was no significant decline in Langfang and Baoding. Regarding the result of ARDL, we found that, except for Langfang and Baoding, the relationship between air quality of cities significantly decreased as the pandemic became worse. It illustrates that, unlike Baoding and Langfang, industrial production increased the air pollution relationship between Beijing and the other three cities. The existing policies consistently implemented synchronous production restrictions in the Beijing-Tianjin-Hebei region, but in fact, the restriction policies implemented on Baoding and Langfang affected economic development but had little effect on the air governance of Beijing. Therefore, the joint prevention and control regulation of air pollution contributes to improving air quality and realizing sustainable cities, but more targeted policies should be formulated.

Based on the above conclusions and the status quo of Beijing, we propose the following implications for Beijing’s air governance: First, it is still necessary to adjust the industrial layout of Tianjin, Zhangjiakou and Chengde, and industrial enterprises with severe pollution should be relocated and equipped with efficient pollution treatment facilities. Second, the restriction policies in Tianjin, Zhangjiakou and Chengde are essential when the air quality in these regions is poor. However, the authorities should release the restriction of the production in Baoding and Langfang since even if Baoding and Langfang reduce industrial activities, it would not significantly improve Beijing’s air quality. In order to realize sustainable development, targeted restriction policies are needed.

Declaration of Competing Interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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Conflicts of Interest

The authors declare no conflict of interest.

Data and availability

All the codes and data produced by this work will be available upon request to the authors.

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