Article

Interaction among Air Pollution, National Health, and Economic Development

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Abstract: This paper constructs a vector autoregressive (VAR) model and vector error correction (VECM) model, analyzes the air pollution, economic development, and national health of China from 1990 to 2019, and evaluates the economic losses from the respiratory diseases caused by air pollution. The results show that: (1) China’s economy continues to grow, and the corresponding amount of exhaust gas emissions (during the study period) showed a trend of first increasing and then slowly decreasing. (2) The overall burden of respiratory diseases in China showed a downward trend, with significant differences in gender and age. (3) A significant long-term equilibrium relationship existed between per capita gross domestic product (PGDP), exhaust emissions, and the disability-adjusted life years (DALYs) of the respiratory disease burden. Exhaust emissions will bring about short-term fluctuations of PGDP and disease burden DALYs. Air pollution is mainly caused by exhaust gas emissions, and DALYs and PGDP have little effect on air pollution. (4) Indirect economic losses from respiratory diseases caused by air pollution are likely to be long-term and will impose increasing pressure. On the basis of the healthy and sustainable operation of the economic system, the government should effectively prevent environmental health risks and improve the pollution treatment level.

Keywords: vector autoregressive model (VAR); disability-adjusted life years (DALYs); economic development; air pollution; national health

1. Introduction

Since China’s reform and opening up, the country has made great achievements in economic development, but a heavy price has also been paid in environmental losses. Environmental pollution, especially the significant decline in air quality, brings inevitable health losses [1] and negative socio-economic effects. Epidemiological and toxicological studies have confirmed that short-term or long-term exposure to polluted air will increase the morbidity and hospitalization rates of those suffering from respiratory, cardiovascular, neurological, and immune system diseases and the resulting disease burden [2–4]. In addition, air pollution also significantly affects the occurrence of cancer, birth defects, and early death. Until now, the relationship between air pollution and health has mainly been a concern of those in the fields of health science and epidemiology [5–7]. However, in recent years, some researchers in economics, science, and other disciplines have also begun to conduct cross-research on air pollution [8–12]. A large number of studies have explored the relationship between air pollution, health, and/or economic development using different methods at global and regional scales [13–17]. For example, Qi Yu et al. found that environmental pollution has a significant negative impact on national health and economic growth [18]. Zhang L et al. empirically verified that a two-way causal relationship exists between economic growth and air pollution. The study also concluded that excessive pollution would drag down and hinder economic growth, and economic growth will lead to an increase in pollutant emissions [19]. At present, the environmental and health
costs being incurred in the process of economic development have gradually become an important reference standard for the comprehensive evaluation of the quality of economic development. Air pollution inhibits economic growth by affecting the accumulation of human capital and the supply of labor. The process of economic development leads to the discharge of a large number of pollutants, and the technological innovation brought about by economic development plays a positive role in promoting the control of air pollution. The issue of how to balance the relationship between economic development and environmental protection so as to further effectively prevent the adverse health and economic effects caused by air pollution has become particularly important.

Most existing studies have discussed the impact of either economic development or environmental pollution on national health, but very few studies have analyzed the dynamic interaction between the three. In addition, the quantitative measurement of the health-related economic losses caused by pollution is mainly the assessment of direct economic loss; relatively less of the measurement involves the calculation and assessment of indirect economic loss. Therefore, this study constructs a vector autoregressive (VAR) model and a vector error correction (VECM) model to analyze the relationship between economic development, air pollution, and the respiratory disease burden. In order to further investigate the impact response and contribution degree of each variable, impulse response analysis and variance decomposition methods are also introduced in this paper to explore the dynamic interaction between economic development, air pollution, and respiratory disease burden. Efforts are also made to further measure the indirect economic losses due to respiratory diseases caused by air pollution. This study helps to understand the causal relationship and harmful degree of air pollution to a certain extent and thus provides a decision-making basis for balancing the relationship between economic growth, environmental pollution, and improving national health.

2. Materials and methods

2.1. Data Source and Processing

The data in this study come from the «China Statistical Yearbook» and the Global Burden of Disease (GBD) database. The data contain three kinds of timing variables, namely gross domestic product (GDP/billion yuan), gross national income (GNI/billion yuan), and per capita GDP (PGDP/yuan), all of which reflect economic development. Emissions of sulfur dioxide (SO₂/Mt), nitrogen oxides (NOx/Mt), and soot and dust (soot(dust)/Mt) are included in the national exhaust emissions. Disability-adjusted life years (DALYs/person years), deaths (deaths/person years), years of life lost (YLLs/person years) due to diseases or physical disabilities, and years lost due to disability (YLDs/person years) are used to reflect national health. Among them, DALYs is the sum of years lost due to premature death (YLLs) and years lost due to disability (YLDs), so DALYs = YLLs + YLDs (WHO, 2020).

Compared with existing studies [20], this paper has a broader coverage and involves more variables; the variation of variables is shown in Figure 1. In order to eliminate the effect of the magnitude of the data, the descriptive statistics of the three emission indicators of pollutants, the three indicators of economic development, and the four indicators of respiratory disease burden (for a total of 10 variables) are taken as natural logarithms in this paper (Table 1). Overall, the means and medians of the data are relatively close, and the standard errors are relatively small, indicating that the data in this paper are relatively homogeneous.
This study comprehensively applies VECM and VAR models to explore the relationship between economic development, air pollution, and respiratory diseases. Using a single indicator for each of economic development, environmental pollution, and burden of disease would result in a VAR model that provides less information and has omitted variables. Conversely, however, including too many types of variables in the VAR model will lead to unstable model estimation results. Therefore, with reference to existing studies, a total of five indicators of three types of time-series variables, namely economic development, air pollution, and respiratory diseases, are included in the VAR model to construct the VECM model. Since the indicators reflecting the level of economic development are closely related to PGDP, PGDP is used to measure the level of economic development. According to the “three wastes” discharged by national exhaust pollution sources being taken as the main cause of air quality deterioration, the national exhaust emissions (mainly including sulfur dioxide, soot, and dust emissions) in the same period were selected to characterize the degree of air pollution. As a comprehensive indicator, DALYs can thoroughly and accurately assess the time of death and disability of survivors. Therefore, the burden of respiratory diseases DALYs used to characterize the national health level and to empirically analyze the causal relationship between air pollution, national health, and economic development.

The established VAR model with a lag period of $p$ is as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \epsilon_t \quad (t > p)$$  \hspace{1cm} (1)

Here, $y_t = (\text{PGDP}_t, \text{NOx}_t, \text{SO}_2_t, \text{Soot(dust)}_t, \text{DALYs}_t)'$ is the explained variable of period $t$, $\alpha_i (i = 1, \cdots, p)$ is the regression coefficient, $p$ is the lag period, and $\epsilon_t$ is the residual representing the deviation from the long-term relationship.

Through the co-integration test, it is found that the five variables are single second-order integration, indicating that a long-term equilibrium relationship exists between

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnNOx</td>
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<td>7.184</td>
<td>7.797</td>
<td>6.778</td>
<td>0.334</td>
</tr>
<tr>
<td>lnSoot(dust)</td>
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<td>7.505</td>
<td>8.208</td>
<td>6.992</td>
<td>0.303</td>
</tr>
<tr>
<td>lnSO$_2$</td>
<td>7.454</td>
<td>7.581</td>
<td>7.859</td>
<td>6.125</td>
<td>0.453</td>
</tr>
<tr>
<td>lnYLLs</td>
<td>12.675</td>
<td>12.621</td>
<td>13.396</td>
<td>12.12</td>
<td>0.426</td>
</tr>
<tr>
<td>lnDeaths</td>
<td>9.542</td>
<td>9.608</td>
<td>10.365</td>
<td>8.718</td>
<td>0.443</td>
</tr>
<tr>
<td>lnDALYs</td>
<td>12.776</td>
<td>12.725</td>
<td>13.441</td>
<td>12.271</td>
<td>0.39</td>
</tr>
</tbody>
</table>
air pollution, national health, and economic development. Therefore, five co-integration equations are constructed in this paper.

The vector error correction model VECM model is as follows:

\[ \Delta y_t = C + \alpha \times ECM_{t-1} + \sum_{i=1}^{l} \Gamma_i \Delta y_{t-i} + \epsilon_t \]  

(2)

Here ECM_{t-1} is the vector error correction term, and the absolute value of coefficient \( \alpha \) reflects the speed at which the variable is adjusted to the equilibrium state when it deviates from the long-term equilibrium in the short term (referred to as the “adjustment coefficient”). Then, \( \Gamma_i \) is the coefficient matrix of the lag term, \( l \) is the optimal lag order, \( C \) is the vector of the constant term, and \( \epsilon_t \) is the vector of the residual term.

The results of the VECM model show that air pollution, national health, and economic development all have short-term fluctuations, which deviate from the equilibrium state. However, when a variable is disturbed and deviates from the equilibrium state, other factors in the system will act together to make that variable converge to the long-term equilibrium path.

2.3. Economic Burden of Disease

It is important to study the economic loss of health when assessing air pollution risk control. In this study, the modified human capital method is used to measure the indirect economic burden (IEB) of disease. The revised human capital method is the value of a non-market good assessment method, which evaluates the value of human life from a social perspective. Per capita national income and per capita GDP (PGDP) is often used as the contribution of a statistical life year to the relevant society; that is, the value of a statistical life year. For society as a whole, the loss of one statistical life year is the loss of one GDP per capita.

\[ \text{IEB} = \text{PGDP} \times \text{disease burden} \times \text{productivity weight} \]  

(3)

From the perspective of society, air pollution causes illness, disability, and premature death in the population. Air pollution also reduces the human production factors, which naturally leads to the reduction in the contribution of human production factors to GDP. As a result, the whole of society suffers losses. The weight of productivity varies with different age groups. The 0–14 age group did not participate in social wealth creation, and the weight was 0.15. Those aged 15–44 and 45–59 created the most social wealth. Their productivity weights were 0.75 and 0.8, respectively. For people over 60 years old, the productivity weight was 0.1 [21].

Disease indicators (YLLs, YLDs, deaths, and DALYs) for each age group (0–14 years old, 15–44 years old, 45–59 years old, and over 60 years old) were combined, multiplied by productivity weights and GDP per capita, respectively, and finally summed to obtain the indirect economic burden of disease. The indirect health-related economic losses caused by the four indicators of respiratory disease burden, which in turn were caused by air pollution, increased year by year in China from 1990 to 2019.

3. Results and Discussion

In this paper, descriptive statistical analysis, a vector autoregressive (VAR) model, and a vector error correction (VECM) model are comprehensively used to analyze the interactive effects of air pollution, economic development, and the respiratory disease burden in China from 1990 to 2019. In addition, the economic losses resulting from respiratory diseases caused by air pollution are also evaluated.

3.1. Descriptive Statistical Analysis

In this section, descriptive statistical analysis is first used to more intuitively present the national health and economic development status of air pollution from 1990 to 2019 so as to provide a basis for further model analysis.
3.1.1. Time Evolution of China’s Economy and Air Pollution Indicators

China’s GDP and gross national income (GNI) increased from 188.7287 billion yuan and 189.2333 billion yuan in 1990 to 9865.152 billion yuan and 9837.512 billion yuan in 2019, respectively, with growth rates of 98.087% and 98.076%. With regard to the national emissions of each of the air pollutants, the total emissions of indicators rose significantly from 1991 to 1997; from 1998, the total emissions of SO\textsubscript{2} and soot (dust) in national exhaust gases showed a zigzag downward trend (Figure 2). National NO\textsubscript{x} emissions showed a fluctuating increase from 1990 to 2006 [22], followed by a sharp increase from 2006 to 2010 (“11th Five-Year” Plan period), and then a yearly decrease from 2011 to 2019. Industrial sources were the main contributors to the total NO\textsubscript{x} emissions during these years; their share was basically maintained at about 70%. The remaining approximately 30% was mainly contributed by domestic sources, motor vehicle exhausts, and concentrated emissions [23].

![Figure 2. China’s economic development and emissions of SO\textsubscript{2}, NO\textsubscript{x}, and soot (dust), from 1990 to 2019.](image)

From the perspective of time evolution, China’s GDP and GNI have risen continuously from 1990 to 2019. The emission of exhaust gas showed a continuous increase, and then, due to the introduction of the emission reduction policy in the “12th Five-Year Plan”, exhaust gas emissions turned to a slow decline.

3.1.2. Time Evolution of Respiratory Diseases in China

In this study, seven types of chronic respiratory diseases caused by air pollution are selected to represent the nation’s health: namely (1) otitis media, (2) chronic respiratory diseases, (3) chronic obstructive pulmonary disease (COPD), (4) lower respiratory effects, (5) respiratory infections and tuberculosis, (6) tracheal bronchus and lung cancer, and (7) upper respiratory effects.

Pollution-induced respiratory diseases recorded from 1990 to 2019 are shown in Figure 3. In general, except for tracheal bronchus and lung cancer, the other six types of respiratory diseases showed a year-on-year decline. Among them, lower respiratory tract infection and respiratory tract infection, and tuberculosis were the two types of diseases with the most significant decline in the past 30 years. Meanwhile, otitis media and upper respiratory tract infection accounted for the lowest proportions of the seven types of respiratory diseases. Tracheal bronchus and lung cancer increased by 51.57 percent, going from 126,648 person-years in 1990 to 261,494 person-years in 2019. Compared with the DALYs in 1990, the DALYs of chronic obstructive pulmonary disease, otitis media, respiratory tract in-
Infection, and tuberculosis increased by 364.8, 16,985.6, and 273.8 person-years, respectively, in 2019. The DALYs of the other four diseases, including lower respiratory tract infection, chronic respiratory system disease, tracheal bronchus, lung cancer, and upper respiratory tract infection, decreased by 11,848.6, 3325.4, 36,261.9, and 107,241.8 person-years, respectively. In terms of deaths, chronic obstructive pulmonary disease, lower respiratory tract infection, otitis media, and respiratory tract infection, tuberculosis increased by 66,261.6, 223.7, 247.2, and 762.8 person-years, respectively, in 2019. The other three diseases, namely chronic respiratory disease, tracheal bronchus, lung cancer, and upper respiratory tract infection decreased by 80,938.1, 332.2, and 5740.1 person-years, respectively.

In general, the DALYs and YLDs of the four indicators of the burden of respiratory diseases in China in the past 30 years (Figure 3h) have shown a significant downward trend. The DALYs decreased from 971,919 person-years in 1990 to 110,690 person-years in 2019, a decrease in 88.6%, representing an average annual decrease in 2.95%. Deaths and YLLs fluctuated significantly year-by-year from 1990 to 2019, with no significant upward or downward trend.

Indicators of Respiratory Diseases by Gender Group

The disease burden caused by air pollution from 1990 to 2019 was grouped by gender in order to observe the change in the disease burden of patients of different genders (Figure 4).
Figure 3. Respiratory diseases were caused by seven types of air pollution in China from 1990 to 2019. (a) otitis media, (b) chronic respiratory diseases, (c) chronic obstructive pulmonary disease (COPD), (d) lower respiratory effects, (e) respiratory infections and tuberculosis, (f) tracheal bronchus and lung cancer, (g) upper respiratory effects, and (h) annual average changes of respiratory diseases.

As shown in Figure 4, female YLLs decreased from 624,802.2 person-years in 1990 to 139,927.7 person-years in 2019, a decrease in 77.6%. Male YLLs decreased from 690,102.1 person-years in 1990 to 227,148.6 person-years in 2019, a decrease in 67.08%. The average annual decrease in male and female DALYs was 2.85% and 3.07%, respectively. In 1990, there were 25,320.26 male deaths per year and 26,310.11 female deaths, or 989.85 fewer male deaths than female deaths. In 2019, there were 7789.6 male deaths and 4730.77 female deaths, or 3058.82 more male deaths than female deaths. In 1990, the male YLDs were 20,940.88 person-years, while the female YLDs were 35,955.52 person-years, meaning there were 15,014.64 fewer male YLDS than females. In 2019, male YLDs were 19,529.72 person-years, and female YLDs were 31,771.45 person-years, so there were 12,241.73 fewer person-years for males than females (Figure 4).

In general, from 1990 to 2019, the YLLs and DALYs of male and female respiratory diseases showed a significant downward trend year by year. The deaths and YLDs of men and women alternately rose and fell year-by-year, with certain volatility, and the trend of increase or decrease was not significant. In the past 30 years, the number of YLLs, DALYs, and deaths in males was higher than in females.
there were 15,014.64 fewer male YLDS than females. In 2019, male YLDs were 19,529.72 person-years, and female YLDs were 31,771.45 person-years, so there were 12,241.73 fewer person-years for males than females (Figure 4).

Respiratory Diseases by Age Group

The disease burden due to air pollution from 1990 to 2019 was grouped by age to observe the changing status of disease burden in patients of different ages (Figure 5). Comparing different age groups from 1990 to 2019, the performance of different disease burden indicators varied among different age groups. In addition, the overall trend of decreasing respiratory disease burden YLLs and DALYs in China occurred year-by-year, and the age groups of 0–14 years and 60 years or older were the groups with the highest risk of air pollution-induced disease DALYs and YLLs. Among them, in 1990, DALYs achieved a peak of 2,444,112 person-years in the 0–14 years age group, followed by 641,613 person-years in the 60 year and older age group. In contrast, no significant age differences were found in YLDs and deaths due to respiratory diseases, and there was no clear pattern of risk across age groups. Compared with 1990, the number of YLLs and DALYs in China in 2019 was significantly lower in the 0–14 age group, the YLDs decreased in the 45–59 years group, and deaths significantly decreased in the over-60 years age group.

Overall, significant age differences existed in respiratory disease burden, with a significantly higher respiratory disease burden in the 0–14 and 60+ age groups than in other age groups.
of risk across age groups. Compared with 1990, the number of YLLs and DALYs in China in 2019 was significantly lower in the 0–14 age group, the YLDs decreased in the 45–59 years group, and deaths significantly decreased in the over-60 years age group.

Figure 5. (a) The age group of indicators of respiratory disease indicator DALYs, (b) age group of indicators of respiratory disease indicator YLLs, (c) age group of indicators of respiratory disease indicator Deaths, and (d) age group of respiratory disease indicator YLDs.

3.2. Empirical Analysis of the Interaction between Air Pollution, National Health, and Economic Development

In order to make the conclusions of this study credible, the stationarity test and cointegration test are first carried out.

3.2.1. Stationarity Test

The stationarity test of variables is the basis of an empirical test. In order to avoid the pseudo-regression phenomenon, augmented Dickey-Fuller (ADF) was used to test PGDP, soot (dust) emissions, NOx emission, SO2 emission, and DALYs. Since all five variables were compressed using logarithms, the influence of heteroscedasticity was excluded. The ADF unit root test results of each variable are shown in Table 2. The original sequence and logarithmic data of each variable cannot pass the ADF test at any significance level, but their second-order difference is stable at the significance level of 5%. This finding indicates that a co-integration relationship may exist between the five variables.

3.2.2. Granger Causality Test

In order to study the mutual influence of variables and examine the joint significance of equation coefficients, this paper conducted a Granger causality test (GCT) [24] based on the VAR model.
Table 2. ADF test results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Value</th>
<th>p-Value</th>
<th>10% Level</th>
<th>Form of Inspection (c, t, k)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PGDP</td>
<td>3.2849</td>
<td>1.0</td>
<td>−2.646</td>
<td>Non-stationarity</td>
</tr>
<tr>
<td>ΔPGDP</td>
<td>−6.6832</td>
<td>0.0</td>
<td>−2.63</td>
<td>Stationarity</td>
</tr>
<tr>
<td>lnPGDP</td>
<td>−2.2472</td>
<td>0.1896</td>
<td>−2.646</td>
<td>Non-stationarity</td>
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<td>ΔlnPGDP</td>
<td>−3.239</td>
<td>0.0178</td>
<td>−2.633</td>
<td>(0, 0, 4)</td>
</tr>
<tr>
<td>NOx</td>
<td>−2.4665</td>
<td>0.1238</td>
<td>−2.625</td>
<td>Non-stationarity</td>
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<td>ΔNOx</td>
<td>−4.4432</td>
<td>0.0002</td>
<td>−2.628</td>
<td>Stationarity</td>
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<tr>
<td>lnNOx</td>
<td>−2.0331</td>
<td>0.2723</td>
<td>−2.63</td>
<td>Non-stationarity</td>
</tr>
<tr>
<td>ΔlnNOx</td>
<td>−4.4976</td>
<td>0.0002</td>
<td>−2.628</td>
<td>(0, 0, 4)</td>
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<tr>
<td>Soot(dust)</td>
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<td>0.5103</td>
<td>−2.623</td>
<td>Non-stationarity</td>
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<tr>
<td>ΔSoot(dust)</td>
<td>−7.5407</td>
<td>0.0</td>
<td>−2.628</td>
<td>Stationarity</td>
</tr>
<tr>
<td>lnSoot(dust)</td>
<td>−1.1879</td>
<td>0.6788</td>
<td>−2.623</td>
<td>Non-stationarity</td>
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<tr>
<td>ΔlnSoot(dust)</td>
<td>−8.1095</td>
<td>0.0</td>
<td>−2.628</td>
<td>(0, 0, 4)</td>
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<td>SO₂</td>
<td>0.2132</td>
<td>0.973</td>
<td>−2.623</td>
<td>Non-stationarity</td>
</tr>
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<td>ΔSO₂</td>
<td>−7.4668</td>
<td>0.0</td>
<td>−2.628</td>
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<td>ΔlnSO₂</td>
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<td>0.0</td>
<td>−2.628</td>
<td>(0, 0, 4)</td>
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<td>DALYs</td>
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<td>0.0482</td>
<td>−2.643</td>
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<td>lnDALYs</td>
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<td>0.6134</td>
<td>−2.636</td>
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</tr>
<tr>
<td>ΔlnDALYs</td>
<td>−3.0845</td>
<td>0.0277</td>
<td>−2.643</td>
<td>(0, 0, 4)</td>
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</tbody>
</table>

Note: Test form (c, t, k), where c is the constant term, t is the trend term, k is the number of lag periods, and Δ is the second-order difference.

Determination of Model Lag Order

The ADF test results show that the vector autoregression model can be established. The lag order of the model has a great impact on the research results, so the lag order should be checked before setting the model. Therefore, the Akaike information criterion (AIC) [25], Bayesian information criterion (BIC) [26], final prediction error criterion (FPE) [27], and Hannan Quinn information criterion (HQIC) [28] are used to determine the lag order in this paper. The results are shown in Table 3. According to the minimum value rule, the optimal lag order is selected as four stages.

Table 3. Determination results of lag order.

<table>
<thead>
<tr>
<th>Lag</th>
<th>AIC</th>
<th>BIC</th>
<th>FPE</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>77.36</td>
<td>77.6</td>
<td>3.96 × 10^{13}</td>
<td>77.43</td>
</tr>
<tr>
<td>1</td>
<td>67.73</td>
<td>69.18</td>
<td>2.71 × 10^{29}</td>
<td>68.15</td>
</tr>
<tr>
<td>2</td>
<td>67.02</td>
<td>69.68</td>
<td>1.70 × 10^{29}</td>
<td>67.79</td>
</tr>
<tr>
<td>3</td>
<td>65.81</td>
<td>69.68</td>
<td>1.058 × 10^{29} *</td>
<td>66.92</td>
</tr>
<tr>
<td>4</td>
<td>63.71 *</td>
<td>68.79 *</td>
<td>1.06 × 10^{29} *</td>
<td>65.17 *</td>
</tr>
</tbody>
</table>

Note: * in the table represents the selection result of this criterion.

Granger Causality Analysis

According to the GCT test results (Supplementary Table S1), at the significance level of 5%, the hypothesis that PGDP is not the Granger cause of pollutant emission growth and the hypothesis that pollutant emission is not the Granger cause of respiratory disease burden DALYs are both rejected. The hypothesis that DALYs are not the Granger cause of PGDP is rejected at the significance level of 1%. The hypothesis that pollutant emissions are not the Granger causes of PGDP is rejected at a significance level of 5%. That is, exhaust emissions are the Granger cause of DALYs, and a two-way causal relationship exists between exhaust emissions and per capita GDP, as well as between per capita GDP and DALYs.

In general, economic growth is the Granger cause of air pollution and respiratory diseases, but the impact of economic growth on air pollution and respiratory diseases is
not significant. Air pollution may be the Granger consequence of economic development and respiratory disease. Air pollution causes respiratory diseases and further affects human capital accumulation, labor supply, and labor productivity, thereby constraining economic growth.

3.2.3. Cointegration Test

Although the data pertaining to air pollution, respiratory disease, and economic development are non-stationary series, one can expect that the five variables will not indefinitely deviate from each other. This study considers that the cointegration method can analyze the quantitative relationship of several non-stationary economic variables and can also judge whether a long-term equilibrium relationship exists between the variables. Five variables reflecting air pollution, respiratory diseases, and economic development are adopted in this paper, and a Johansen cointegration test [29] is applied to test the cointegration relationship of multiple variables. Therefore, the above non-stationary but second-order mono-integration sequences are tested in this study. The results are shown in Table 4.

Table 4. Results of the Johansen cointegration test.

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Trace Statistics Value</th>
<th>Critical (10%)</th>
<th>Critical (5%)</th>
<th>Critical (1%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>293.1304</td>
<td>75.1027</td>
<td>79.3422</td>
<td>87.7748</td>
</tr>
<tr>
<td>At most 1</td>
<td>152.1399</td>
<td>51.6492</td>
<td>55.2459</td>
<td>62.5202</td>
</tr>
<tr>
<td>At most 2</td>
<td>77.2505</td>
<td>32.0645</td>
<td>35.0116</td>
<td>41.0815</td>
</tr>
<tr>
<td>At most 3</td>
<td>43.9297</td>
<td>16.1619</td>
<td>18.3985</td>
<td>23.1485</td>
</tr>
<tr>
<td>At most 4</td>
<td>12.9096</td>
<td>2.7055</td>
<td>3.8415</td>
<td>6.6349</td>
</tr>
</tbody>
</table>

As can be seen from Table 4, the trace statistical value of 12.9096 is higher than 6.6349, showing that the null hypothesis of “at most four cointegration relationships” is rejected at the 1% level. Also, there are five cointegration relationships among PGDP, DALYs, soot (dust) emissions, NOx emissions, and SO2 emissions; this finding is in line with the VAR hypothesis. In other words, a long-term equilibrium relationship exists between air pollution, respiratory disease burden DALYs and economic development.

3.2.4. VAR-VECM Model Analysis

Based on the stationarity test and co-integration test analysis, this study constructed a VAR-VECM model to analyze the interaction between air pollution, national health, and economic development.

Results of Cointegration Equation

Johansen’s estimation results show that there are five cointegration equations among the variables. In lines 3, 4, 5, 6, and 7 of Table 5, one can estimate the cointegration equation in which NOx, soot (dust), SO2, PGDP, and DALYs, respectively, are independent variables. The coefficients of all variables in the table passed the significance test, further verifying the long-term equilibrium relationship between air pollution, respiratory diseases, and economic growth at the significance level of 1%. In the long run, the long-term equilibrium relationship between air pollution, economic development, and respiratory diseases is significant and is mainly influenced by air pollution variables. This is basically consistent with the following variance decomposition analysis, that is, the prediction variance of economic growth and respiratory disease burden is mainly affected by air pollution. Air pollution is mainly affected by exhaust emissions, and the contribution of economic development and disease burden to its prediction variance is relatively small.
were both positive and statistically significant. These findings indicate that these two
variables deviated from the equilibrium state by a large degree and therefore had a greater
impact on repairing the equilibrium state. Eventually, they will return to the
long-run equilibrium path.

For ECM\(_{2,1}^{-1}\), the adjustment coefficients of PGDP (coefficient 0.0171), DALYs (co-
efficient 0.0009), and SO\(_2\) (coefficient 1.912) are all positive. Soot (dust) (coefficient
−0.797) and NOx (coefficient of −2.4006) showed negative error correction coefficients.
These findings show that SO\(_2\) deviated from the equilibrium state to a relatively large
degree, while other variables had no deviation, or the degree of deviation was small. In
ECM\(_{3,1}^{-1}\), ECM\(_{4,1}^{-1}\), all five variables deviated from the equilibrium state, but the deviation
was small, so the influence on the restoration of the equilibrium state was not significant.

For ECM\(_{5,1}^{-1}\), the adjustment coefficients of NOx (coefficient −313.1633), DALYs (co-
efficient −0.1936), and SO\(_2\) (coefficient −30.5128) were all negative. Meanwhile, the
adjustment coefficients of PGDP (coefficient 23.2972) and soot (dust) (coefficient 115.29)
were both positive and statistically significant. These findings indicate that these two
variables deviated from the equilibrium state by a large degree and therefore had a greater
impact on repairing the equilibrium state.

In general, when a variable is disturbed and deviates from the equilibrium state, air
pollution, economic growth, and other factors of respiratory disease burden will work
together to converge to the long-run equilibrium path. Eventually, they will return to the
long-run equilibrium path.

### Impulse Response Analysis

Based on the VECM model, impulse response curves were further described to rep-
resent the dynamic relationship between air pollution, economic growth, and respiratory
diseases (Figure 6). As shown in Figure 6, the horizontal axis is the number of lag periods,
and the maximum number of response periods selected in this study is 10. The vertical
axis is the intensity of impulse response. The blue line represents the result of the impulse
response, and the dotted line on both sides represents the 95% horizontal confidence in-
terval. When the value of the impulse function is less than 0, this means that the impact
variable has a negative impact on the response variable. When the value of the impulse
function is greater than 0, this means that the impact variable has a positive impact on the

**Table 5. Results of Var-VECM model (Part).**

<table>
<thead>
<tr>
<th>Variable</th>
<th>NOx</th>
<th>Soot (Dust)</th>
<th>Coefficient</th>
<th>PGDP</th>
<th>DALYs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.03 × 10(^{-16}) **</td>
<td>0.0690</td>
<td>−0.2728</td>
<td>0.0061</td>
<td>0.0004</td>
</tr>
<tr>
<td>NOx</td>
<td>−5.01 × 10(^{-16}) **</td>
<td>−0.797 *</td>
<td>1.912 **</td>
<td>0.0171</td>
<td>0.0009</td>
</tr>
<tr>
<td>Soot (dust)</td>
<td>2.57 × 10(^{-16}) **</td>
<td>−1.16 × 10(^{-16}) **</td>
<td>5.6216 * 0.2728</td>
<td>0.0061</td>
<td>0.0004</td>
</tr>
<tr>
<td>SO(_2)</td>
<td>−6.82 × 10(^{-16}) **</td>
<td>−5.57 × 10(^{-15}) **</td>
<td>−4.96 × 10(^{-18})</td>
<td>−2.79 × 10(^{-17}) **</td>
<td>−1.53 × 10(^{-14}) **</td>
</tr>
<tr>
<td>PGDP</td>
<td>−4.31 × 10(^{-19}) **</td>
<td>−5.37 × 10(^{-15}) **</td>
<td>−4.96 × 10(^{-18})</td>
<td>−2.79 × 10(^{-17}) **</td>
<td>−1.53 × 10(^{-14}) **</td>
</tr>
<tr>
<td>DALYs</td>
<td>0.2211</td>
<td>0.0690</td>
<td>−0.2728</td>
<td>0.0061</td>
<td>0.0004</td>
</tr>
<tr>
<td>ECM(_{2,1}^{-1})</td>
<td>−2.4006 *</td>
<td>−0.797 *</td>
<td>1.912 **</td>
<td>0.0171</td>
<td>0.0009</td>
</tr>
<tr>
<td>ECM(_{3,1}^{-1})</td>
<td>1.4966 *</td>
<td>0.5543 *</td>
<td>−1.6337 *</td>
<td>−0.0117</td>
<td>0.0006</td>
</tr>
<tr>
<td>ECM(_{4,1}^{-1})</td>
<td>5.1988 *</td>
<td>1.0624 **</td>
<td>−5.6216 *</td>
<td>0.1972 *</td>
<td>0.0061</td>
</tr>
</tbody>
</table>
| ECM\(_{5,1}^{-1}\) | −313.1633 | 115.29 ** | −30.5128 | 23.2972 * | −0.1936

Note: * means 0.05, and ** means 0.1.

The last five rows of Table 5, respectively, present the estimation results of the VECM
model for five variables (part). The error correction coefficient indicates the adjustment of
the long-term equilibrium relationship to the short-term change. Short-term changes in air
pollution, economic growth, and the burden of respiratory disease interact. Specifically,
ECM\(_{1,1}^{-1}\), the error correction coefficients of NOx (coefficient 0.2211), soot (dust) (co-
efficient 0.0690), PGDP (coefficient 0.0061), and DALYs (coefficient 0.0004) are positive, while the
adjustment coefficient of SO\(_2\) (coefficient −0.2728) is negative. Almost all coefficients
were not statistically significant, indicating that the emission of SO\(_2\) did not deviate from
the equilibrium state, and the other four variables had only a slight deviation from the
equilibrium state. Therefore, the influence on the restoration of the equilibrium state was
not very great.

For ECM\(_{2,1}^{-1}\), the adjustment coefficients of PGDP (coefficient 0.0171), DALYs (co-
efficient 0.0009), and SO\(_2\) (coefficient 1.912) are all positive. Soot (dust) (coefficient
−0.797) and NOx (coefficient of −2.4006) showed negative error correction coefficients.
These findings show that SO\(_2\) deviated from the equilibrium state to a relatively large
degree, while other variables had no deviation, or the degree of deviation was small. In
ECM\(_{3,1}^{-1}\), ECM\(_{4,1}^{-1}\), all five variables deviated from the equilibrium state, but the deviation
was small, so the influence on the restoration of the equilibrium state was not significant.

For ECM\(_{5,1}^{-1}\), the adjustment coefficients of NOx (coefficient −313.1633), DALYs (co-
efficient −0.1936), and SO\(_2\) (coefficient −30.5128) were all negative. Meanwhile, the
adjustment coefficients of PGDP (coefficient 23.2972) and soot (dust) (coefficient 115.29)
were both positive and statistically significant. These findings indicate that these two
variables deviated from the equilibrium state by a large degree and therefore had a greater
impact on repairing the equilibrium state.

In general, when a variable is disturbed and deviates from the equilibrium state, air
pollution, economic growth, and other factors of respiratory disease burden will work
together to converge to the long-run equilibrium path. Eventually, they will return to the
long-run equilibrium path.
response variable. In particular, this is the effect of short-term residual shocks, which are not necessarily consistent with long-term equilibrium coefficients.

Figure 6. Impulse response analysis of “three waste” emissions, PGDP growth, and disease burden DALYs.

As can be seen from the pulse diagram of DALYs caused by the discharge of “three wastes,” the blue pulse line fluctuates significantly. This indicates that under the exogenous impact of one standard deviation unit, the increase in “three waste” emissions have a strong impact on the burden of respiratory disease DALYs. In addition, the positive and negative impacts fluctuate significantly, and the impact lasts a long time. The impact of soot(dust) emission on DALYs also reached positive peak values in the 4th and 7th periods. At the beginning of the impact of NOx and SO$_2$ emissions, DALYs had no immediate impulse response, and there was a certain lag. Overall, the cumulative effect of emissions is an increase in the burden of respiratory diseases; there is also a lag in the negative effects of air pollution on respiratory diseases. The increase in per capita GDP has a relatively long-term and strong impact on the burden of respiratory diseases’ DALYs. The reason behind this finding may be that a great correlation exists between economic growth and exhaust emissions, and the adverse economic effects (such as the increase in exhaust emissions brought about by economic development) will aggravate the burden of respiratory diseases.

As can also be seen from the figure, the increase in the economic burden of diseases’ DALYs has a positive impact on economic growth. However, the impact intensity is small, indicating that the increase in the burden of respiratory diseases will hinder economic growth to some extent, but again, the impact is very small. Since exhaust emissions mainly come from industrial production, the increase in exhaust emissions, to some extent, can be considered to represent the increase in output, thus promoting economic development. However, the negative impacts brought about by exhaust emissions (such as climate change,
national health, and even the loss of labor resources) also have a significant negative impact on the economy. What’s more, this impact will become more prominent in the later period. The pulse diagram shows that the impact of three waste emissions on PGDP is positive or negative, with a long duration but low intensity, and gradually converges to 0.

The increase in the emissions of “three wastes” has a large impact on itself and on each other, and the impact lasts for a long time. This finding is consistent with the conclusion of the variance decomposition analysis, namely that pollutants are mainly affected by exhaust emissions. The increase in per capita GDP has a significantly positive impact on pollutant emissions. The impact probably peaks around the third period and then gradually weakens and turns into a negative impact. This result is basically similar to the conclusions found in existing studies [30,31]. Economic development leads to more and more pollutant emissions, but when economic growth reaches a threshold, economic growth’s positive impact on pollutant emissions gradually weakens and even turns negative. Some studies [32] have maintained that, although the process of economic growth will increase the emission of air pollutants, the technological progress of industrial units and the high-level evolution of industrial structures will significantly inhibit the emission of air pollutants.

Variance Decomposition Analysis

The long-term equilibrium, short-term perturbation, and causality of pollutant emissions, economic growth, and respiratory diseases have been analyzed. After a unit root test, the second-order difference of all variables is known to be stable. Therefore, in order to investigate the short-term impact between variables, a VAR model with the optimal lag order of variables of 4-order is used in this paper for variance decomposition. The purpose of variance decomposition is to analyze the contribution of each variable to the change of other variables so as to better understand the interaction between variables (Figure 7).

According to the results in Figure 7, if the growth rate of PGDP is predicted one period ahead, 62.96% of the forecast variance comes from PGDP itself, while 31.46%, 2.63%, and 2.96% come from the emission growth of SO$_2$, smoke dust, and NOx, respectively. The DALYs have no influence on the growth rate. If the prediction is made 10 periods ahead, only 1.68% of the predicted variance comes from itself, while 65.46%, 31.08%, 1.08%, and 0.71% come from NOx, SO$_2$, soot (dust) emissions, and DALYs, respectively. In the short term, PGDP growth is mainly influenced by itself, and the degree of impact of pollutant emissions on PGDP growth gradually increases as the projection period increases. The impact of DALYs on PGDP is negligible.

If the burden of disease DALYs is predicted one stage ahead, the predicted variance is 20.07% from its own, while 0.43%, 0.89%, and 65.44% are from the emissions of SO$_2$, NOx, and smoke dust, respectively; 13.17% is from the growth of PGDP. When the number of lag periods is increased, the soot (dust) emissions, PGDP, and DALYs experience a small decrease, while the NOx and SO$_2$ emissions significantly increase. If the prediction is made 10 periods ahead, 1.74% of the forecast variance comes from itself, while 19.54%, 32.98%, 35.72%, and 10.02% of the forecast variance come from SO$_2$, NOx, soot (dust) emissions, and PGDP, respectively. The finding indicates that the growth of disease burden DALYs is mainly affected by pollutant emissions and also has a certain degree of influence on itself and PGDP.

If the soot (dust) emission is predicted one stage ahead, 87.53% of the predicted variance comes from itself, and 12.47% comes from NOx emissions, while SO$_2$, PGDP, and DALYs have no influence on the predicted variance. However, as the number of lag periods increased, the influence of NOx, SO$_2$ emissions, PGDP growth rate, and respiratory disease burden DALYs also gradually increased. Meanwhile, the proportion of the soot (dust) emission growth rate decreased. If the prediction is made 10 periods ahead, 27.14% of the forecast variance comes from itself, while 47.94%, 12.99%, 1.88%, and 10.04% of the forecast variance come from NOx, SO$_2$, DALYs, and PGDP, respectively. These findings show that the growth of soot (dust) emissions is mainly influenced by other exhaust emissions and its
own and is also influenced by PGDP. The growth rates of SO$_2$ and NOx emissions are also largely influenced by their own and other emissions.

Figure 7. Variance decomposition results from 10 lag periods.
In general, respiratory diseases are mainly caused by exhaust emissions. With the increase in the forecast period, the impact of pollutant emissions on GDP growth gradually increases. Exhaust emissions are mainly affected by other exhaust emissions, but economic development also has a certain degree of influence. That is, air pollution is an important variable in the prediction variance of economic growth and respiratory diseases. Air pollution is mainly affected by exhaust emissions, and the contribution of national health and economic development to the prediction variance of air pollution indicators is relatively small.

Increased pollution will lead to an increase in the respiratory disease burden, i.e., the more serious the air pollution is, the heavier the respiratory disease burden will be and the more detrimental to the improvement of health status. Increased pollution also leads to adverse economic effects, a finding which is consistent with those of previous studies [33]. In short, better health levels can promote virtuous economic development, and healthy people tend to be more productive than sick people [34]. In the long term, ignoring the cumulative effects of air pollution will become even more serious. Emissions and air pollution will not only affect respiratory diseases and socioeconomic development in the current year but will also have a significant impact on the health of the population and economic development in later years.

Robustness Analysis

Considering the synergies and interrelationships between air pollution, health, and economic growth, further robustness tests were conducted. The tests explore whether the addition of new data or the selection of different data starting periods and the selection of different lag periods will have a significant effect on the model estimation.

1. This study finds that air pollution did have a negative impact on per capita GDP and disease burden DALYs. The more serious the air pollution was, the more detrimental to the improvement of the economic development level. When the economic development indicators (GNI and GNP) and disease burden indicators (YLDs, deaths, and YLLs) were further introduced, the influence coefficient of pollution on per capita GDP was found to decrease to different degrees, while the influence coefficient of pollution on DALYs changed only slightly. The results show that the addition of new data has no significant effect on the model estimation.

2. The data from 1995 to 2015 were used for modeling, and the corresponding results obtained in the previous section have been compared and analyzed (Supplementary Table S4 and Supplementary Figures S1 and S2). The results show that the selection of different starting periods does not have a significant effect on the model estimation.

3. Considering that the lag order of endogenous variables has a relatively large influence on the freedom of parameter estimation, each increase in the lag order of endogenous variables in this model will lead to the loss of several degrees of freedom. Above, the variable lag order $p$ in the VAR model is set as 4-order. In order to save the degree of freedom, when the lag order $p = 1, 2, 3$, this has little influence on the calculation of variables.

This indicates that the VAR and VECM models constructed in this study have strong robustness, and the test is reliable.

3.3. Assessment of Health Economic Loss

In the previous sections, VAR and VECM models were constructed to analyze the long-term cumulative effects and short-term fluctuations of air pollution on economic development and national health. In reality, compared with short-term fluctuations, the long-term cumulative effect of air pollution cannot be ignored. The facts are that air pollution will not only affect the respiratory diseases and social and economic development of the current year but will also have a significant impact on the health and economic development of residents in later periods. This section will actually measure the economic losses caused by respiratory diseases, which in turn have been caused by air pollution in
the 30 years from 1990 to 2019. The intention is to specifically quantify the adverse health and economic effects of air pollution.

Air pollution seriously damages health and increases the burden of disease, while the heavier and heavier burden of the disease means the loss of a healthy labor force and the diminished social value of the labor force. This will not only hinder the normal growth of the economy but will also require additional investment in social health resources for disease treatment and rehabilitation. In short, air pollution causes serious and direct social and family economic burdens. In a sense, although the direct economic burden of disease is the direct economic expenditure of society and families, the indirect economic burden is the embodiment of the decline in the value of the labor force. This decline can better reflect the reduction in the effective working hours and working capacity of the social labor force, more accurately reflecting the extent of damage to society caused by disease.

In this study, the indirect economic burden of respiratory diseases in China from 1990 to 2019 is estimated. This is achieved by combining the disease indicators YLLs, YLDs, deaths, and DALYs with human capital, based on the different productivity weights given by the differences in the per capita gross national product (PGDP) and the social value created by different age groups. The indirect economic losses of the four disease burden indicators of respiratory diseases, namely YLLs, YLDs, deaths, and DALYs, reached the maximum in the age group of 45–59 years; the losses were 1.854, 0.562, 0.239, and 5.213 billion yuan, respectively (Supplementary Table S2). One possible reason for this result is that the 45–59 age group is at the peak of life and career, with a heavy family-work burden and multiple physical, mental, and economic pressures. At the same time, interpersonal communication is at its most frequent. There is more social interaction, these people often drink and smoke, and the body is in a sub-healthy state [35].

As shown in Figure 8 and Supplementary Table S3, the indirect economic burden caused by the four indicators of respiratory diseases, namely YLLs, YLDs, deaths, and DALYs, was 0.268, 0.111, 0.014 and 0.535 billion yuan, respectively, in 1990. In 2019, the indirect economic burden caused by the same four disease indicators was 2.269, 0.757, 0.175, and 3.678 billion yuan, respectively, representing a respective increase of 88%, 99%, 92%, and 85%, compared with 1990. From 1990 to 2019, the indirect economic losses due to the YLLs, YLDs, deaths, and DALYs caused by four kinds of respiratory diseases, which in turn were caused by air pollution, were [0.268, 2.269], [0.002, 1.791], [0.005, 0.376] and [0.271, 8.879] billion yuan, respectively.

![Figure 8. Economic losses from respiratory diseases, 1990–2019.](image-url)
Over the past 30 years, the economic losses caused by DALYs reached a maximum of 8.879 billion yuan in 2014. A maximum of 1.791 million yuan for YLDS and a maximum of 0.376 million yuan for deaths were recorded in 2015, and the economic losses caused by YLLs reached 2.269 billion yuan in 2019. Overall, the indirect economic losses due to health caused by pollution increased year-by-year from 1990 to 2019. Although the central and eastern parts of China endured a serious haze event in December 2013, since the “Twelfth Five-Year Plan,” by strictly implementing various prevention measures (such as energy-saving and emission reduction measures), emission levels have been significantly reduced, and air quality has been greatly improved. Therefore, the increase in the indirect health losses caused by pollution in 2014–2019 may be due to the long-term, persistent and cumulative effects of air pollution on national health.

4. Conclusions and Suggestions

This paper now offers the primary conclusions.

First, as China’s economy continued to grow, its exhaust emissions showed a trend of increasing first and then decreasing slowly. From 1990 to 2019, the overall burden of respiratory diseases in China showed a downward trend, with significant gender and age differences. Males were affected to a significantly greater extent than females, and residents in the 0–14 years and over-60 age groups were affected significantly more than other age groups.

Second, the original time series of the five variables included in the empirical analysis of the VAR-VECM model in this study all contain unit roots. However, after the second-order difference, the variable series becomes stable; that is, all variables are of the same order. A long-term equilibrium exists between air pollution, respiratory diseases, and economic development. Air pollution can cause short-term fluctuations in economic development and national health. Air pollution is an important variable in the variance of economic growth and respiratory disease forecasts. Air pollution is mainly affected by exhaust emissions, and the contribution of economic development and national health to the prediction variance of air pollution indicators is relatively small.

Third, the worsening of pollution will increase the burden of respiratory diseases and further affect economic growth. In turn, the waste gas pollution caused by industrial and agricultural production in the process of economic development will negatively affect the accumulation of human capital, labor supply, and labor productivity, thus restricting economic growth. The average indirect economic loss of respiratory diseases caused by air pollution in China from 1990 to 2019 was 1.095 billion yuan. The overall increase in the indirect health economic losses due to pollution, again from 1990 to 2019, may be due to the continuing impact of the long-term cumulative effects of air pollution on the health of the population.

In conclusion, industrial and agricultural production in the process of economic development causes air pollution, and more importantly, air pollution will not achieve economic growth. Excessive pollution may, in fact, drag down and hinder economic growth. Particularly, the loss of health will further reduce labor supply and labor productivity and will increase the social and indirect economic burden. This study well reflects the problems of national health, economic development, and air pollution and provides the following enlightenment for balancing the relationship between economic growth, environmental pollution, and improving national health:

First, at present, China has entered the “deep water” zone of air pollution, energy conservation, and emission reduction; the marginal cost and total social cost of air quality improvement are increasing. The scientific and technological requirements for further energy transformation and pollution prevention and control measures will be more difficult and expensive than in the past. China must seek a low-cost path of energy conservation and emission reduction to improve air quality based on careful management, scientific and technological innovation, and careful research.
Second, governments at all levels should not only play a macro-control role and formulate policies and regulations on air pollution control, but they should also cooperate and interact effectively with each other to improve the regional cooperation management mechanism. The concept of “a community with a shared future for mankind” should be firmly established, and a multilateral, multi-tiered, and trans-regional cooperation mechanism on transboundary air pollution control should be established. The objective should be to realize information exchange and technical cooperation among all countries in the world and the ultimate realization of meeting global environmental demands.

Third, air pollution prevention and control require more than large-scale government policies, programs, and international treaties. Individual actions are an important part of any successful strategy to reduce global air pollutant emissions. Therefore, the implementation of energy conservation and consumption reduction projects, as part of the national action plan, must be combined with efforts to reduce PGDP energy consumption and exhaust emission intensity.

In addition, attention should be paid to improving the level of medical and health services, rationally allocating health resources, effectively preventing environmental health risks, and improving the treatment level of pollution-related diseases, all with a view to maintaining the healthy operation of the economic system.

5. Patents

There are no patents resulting from the work reported in this study.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15010587/s1, Figure S1: Impulse response analysis of “three waste” emissions, PGDP growth and disease burden DALYs, 1990–2015; Figure S2: Variance decomposition results of 10 lag periods, 1990–2015. Table S1: Granger causality test; Table S2: Economic loss of disease by age group; Table S3: Economic loss of health from respiratory diseases 1990–2019; Table S4: Results of VAR-VECM model from 1990 to 2015.

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