The Empirical Relationship between Mining Industry Development and Environmental Pollution in China

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Abstract: This study uses a vector autoregression (VAR) model to analyze changes in pollutants among different mining industries and related policy in China from 2001 to 2014. The results show that: (1) because the pertinence of standards for mining waste water and waste gas emissions are not strong and because the maximum permissible discharge pollutant concentrations in these standards are too high, ammonia nitrogen and industrial sulfur dioxide discharges increased in most mining industries; (2) chemical oxygen demand was taken as an indicator of sewage treatment in environmental protection plans; hence, the chemical oxygen demand discharge decreased in all mining industries; (3) tax reduction policies, which are only implemented in coal mining and washing and extraction of petroleum and natural gas, decreased the industrial solid waste discharge in these two mining industries.

Keywords: mining industry; environmental pollution; policy; VAR; China

1. Introduction

Mineral resources are the material basis of economic development. In 2014, China’s oil production was 211.41 million tons, gas production was 124.81 billion cubic meters, and production of non-petroleum oils was 8.437 billion tons [1]. Mining promotes China’s economic development. In the past 10 years, the value of the mining industry has increased each year. Except for in 2014, the mining industry added value accounted for more than 4% of the GDP [2–29]. In 2014, it was 58,788 trillion Yuan, nearly four times that in 2005 (Figure 1). Among the mining industries, coal mining and washing accounted for 44.27%, petroleum and natural gas extraction accounted for 19.84%, non-ferrous metal ore mining and processing accounted for 10.80%, ferrous metal ore mining and processing accounted for 15.87%, and non-metal ore mining and processing accounted for 9.22%. Furthermore, mining cities in which the mining industry is the dominant or pillar industry accounted for 34% of cities in China [30].

Mining activities cause great environmental disturbance. A variety of pollutants are generated in the process of ore mining. These pollutants diffuse into the surrounding environment and result in water, air and soil pollution problems. In 2014, 2531.67 million tons of industrial wastewater was discharged by the mining industry, nearly 2.2 times the 2005 amount; 903.6 billion cubic meters of industrial waste gas, nearly 1.3 times the 2005 amount; and 1449.32 million tons of industrial solid waste, nearly 3 times the 2005 amount (Figure 2). The chemical oxygen demand (COD) and ammonia nitrogen (AN) discharged in industrial wastewater were 1857.12 million and 74.31 million tons, respectively. The industrial sulfur dioxide (SO2) discharged in industrial waste gas was 2192.59 million tons [31–44]. To control pollution from mining processes, 86,187.14 million
Yuan were input for remediation of mine environments in 2014. Mining not only promotes economic development in China but also causes serious environmental pollution problems. The type and the degree of pollution vary depending on different mineral resources; hence, analysis of the nexus between industry development and environmental pollution for different mineral resources is important to compare their related environmental pollution problems and analyze the policies that cause the similarities and differences among them.

![Figure 1. Industrial sales value of mining industrial over 2001–2014.](image1)

![Figure 2. Three wastes emissions over 2001–2014.](image2)

However, existing studies on the nexus between the mining industry and environmental pollution primarily focus on mine product consumption and energy minerals, including coal, oil and natural gas, which draw more attention due to the highlight on the greenhouse effect. Among them, the most studies are on coal consumption because it contributes more carbon per ton of oil equivalent than other resources such as oil and natural gas. These studies include Bloch et al. for China [45], Saboori and Sulaiman for Malaysia [46], Tiwari et al. and Ahmad et al. for India [47,48] and Govindaraju and Tang for India and China [49]. These studies all conclude that CO₂ emission is related to coal consumption. Compared with studies on coal consumption, there are fewer studies on oil and natural gas. Alkhathlan and Javid examined the relationship between oil and natural gas consumption and CO₂ emission in Saudi Arabia from 1980 to 2011, finding that they both lead to an increase in CO₂ emissions, and the CO₂ emissions can be reduced if the energy consumption structure switches from...
oil to natural gas [50]. Saboori and Sulaiman studied the relationship between natural gas and CO₂ emission. The results show that they have a positive relationship.

Although there are numerous studies on the environmental pollution resulting from mine product end consumption, studies on the environmental pollution caused by mine product production are few and focus on single minerals. Hence, it is impossible to contrast the differences in environmental pollution problems among different mineral resources or to discover the policies that cause them. For instance, Yu predicted China’s coal production environmental pollution in 2030, indicating that the turning point of the waste production per year will not occur until 2030 and the pollution caused by coal production will not increase to a great extent [51].

This paper uses the vector autoregression (VAR) model to analyze the water, air and solid pollution problems in coal mining and washing, petroleum and natural gas extraction, and non-ferrous metal ore, ferrous metal ore, and non-metal ore mining and processing. Through the establishment of the dynamic relationship between the gross industrial output value and the pollutant discharged in these five types of mining industries, the environmental pollution problems among them are compared and the policies that cause similarities and differences are analyzed. The VAR model has the following two characteristics. First, the estimation of traditional economic methods are based on economic theory and the theory cannot always rigorously describe the dynamic links among variables [52]. Compared with traditional econometric methods, the VAR model does not rely on these “incredible” economic assumptions. Second, the endogenous variables can appear on the right side of the equations well as be placed on the left side of the equation. This is complex for model to estimate and infer the relationship between variables [53]. Nevertheless, it is unnecessary to identify the endogenous and exogenous variables in the VAR model. Hence, it is used by many researchers [54–56] and is adopted in this paper to analyze the issue.

2. Econometric Methodology

2.1. VAR Model

The VAR model, proposed by Sims, is established based on the statistical properties of the data. It appears as the form of multiple simultaneous equations. In each equation, the dynamic relationship between all of the endogenous variable are estimated by the regression, which include the endogenous and the lagged value of endogenous. Moreover, it allows us to consider both long-and short-run restrictions justified by economic considerations [57]. The mathematical expression of the general VAR model is as follows:

\[
y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \cdots + B_q x_{t-q} + u_t, t \in \{-\infty, +\infty\}
\]

where \( y_t, t = 1, T \) is a \( K \times 1 \) time-series vector and \( A \) is a \( K \times K \) parametric matrix. \( x_t \) is an \( M \times 1 \) vector of exogenous variables and \( B \) is a \( K \times M \) coefficient matrix to be estimated. \( u_t \) represents the random error term.

The large lag periods (p and q) makes it possible for the VAR model to reflect all of the dynamic innovations between variables. However, there is a shortage for the longer lag periods in which more parameters need to be estimated and there is a lower degree of freedom. Hence, it is necessary to make a reasonable choice between the lag periods and the freedom. The general principle is to adopt lag periods when the Swartz Criterion (SC) and Akaike Information Criterion (AIC) are the lowest. The formulas of these two statistics are expressed as follows:

\[
AIC = -2l/n + 2k/n
\]

\[
SC = -2l/n + k \ln n/n
\]
where \( k = m (q_d + p_m) \) represents the number of parameters to be estimated. \( n \) is the sample size and meets the following formula:

\[
\ell = -nm(1 + \ln 2\pi) / 2 - n \ln \left[ \det \left( \frac{\sum \epsilon_t \epsilon_t'}{n} \right) \right] / 2
\]

(4)

### 2.2. Stationary Test

Most econometric models require a stable time series of variables. Hence, it is necessary to implement a stationary test before establishing the model for analysis. The unit root test is the standard method for checking if a sequence is stationary. The Augmented Dickey-Fuller (ADF), KPSS (Kwiatkowski Phillips Schmidt Shin) and Dickey-Fuller GLS (DFGLS) tests are three test methods. This paper uses the ADF test, which is the most widely used. Because a lagged difference term of the dependent variables is added into the regression equation, the ADF test can avoid the effects of higher-order serial correlation:

\[
\Delta y_t = \eta y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t \quad t = 1, 2, \ldots, T
\]

(5)

\[
\Delta y_t = \eta y_{t-1} + \alpha + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t \quad t = 1, 2, \ldots, T
\]

(6)

\[
\Delta y_t = \eta y_{t-1} + \delta t + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t \quad t = 1, 2, \ldots, T
\]

(7)

The following assumptions are then tested:

\[
H_0: \eta = 0, \quad H_1: \eta < 0
\]

(8)

The original hypotheses is that the sequence of economic variable has a unit root, and the alternative hypothesis implies that the time series has no unit root. By testing whether the estimated value \( \hat{\eta} \) rejects the null hypothesis, we can determine if the time series has a unit root.

### 2.3. Data Sources

We use annual time-series data from 2001 to 2014 for industrial output value, chemical oxygen demand discharged, ammonia nitrogen discharged, industrial SO\(_2\) discharged and industrial solid wastes discharged in China. To avoid possible heteroscedasticity and multicollinearity problems, we transform all variables into logarithmic and differential form. Data on industrial output value represent the development of the mining industry and were obtained from the China Industry Economy Statistical Yearbook and the China Industry Statistical Yearbook. To eliminate the effect of price change, the industrial output value is calculated at a constant price (price-base year is 2000). The data for chemical oxygen demand discharged, ammonia nitrogen discharged, industrial SO\(_2\) discharged and industrial solid wastes discharged represent the environmental pollution and were obtained from the China Statistical Yearbook on Environment. Among them, the chemical oxygen demand and ammonia nitrogen discharged are used as indicators of water pollution, industrial SO\(_2\) discharged is used as an indicator of air pollution, and industrial solid waste is used as an indicator of solid pollution. The definitions of the variables are shown in Table 1.
3. Empirical Results

3.1. Results of the Unit-Root Tests

The results of the unit root test for all mining industries are presented in Tables 2–6. The results show that the null hypotheses of a unit root are not rejected in all variables but are rejected in their first-order difference at a 10% significance level.

Thus, the variables are not all a stationary sequence, but their first-order difference is a stationary sequence. Thus, the co-integration tests can be conducted.

Table 2. Unit root test results for coal mining and washing.

| Variable | Definition                      | Units of Measure |
|----------|--------------------------------|------------------|
| GIOV     | Gross industrial output value   | yuan             |
| COD      | Chemical oxygen demand discharge| ton              |
| AN       | Ammonia nitrogen discharge      | ton              |
| ISW      | Industrial solid waste         | ton              |
| SO₂      | Industrial sulfur dioxide emission | ton               |

Note: (I, T, K): I is the intercept, T is the trend, L is the lag length, and N is none; * and ** denote the null hypothesis of a unit root rejected at the 10% and 5% significance levels, respectively.

Table 3. Unit root test results for petroleum and natural gas extraction.

| Variable | Definition                      | Units of Measure |
|----------|--------------------------------|------------------|
| GIOV     | Gross industrial output value   | yuan             |
| COD      | Chemical oxygen demand discharge| ton              |
| AN       | Ammonia nitrogen discharge      | ton              |
| ISW      | Industrial solid waste         | ton              |
| SO₂      | Industrial sulfur dioxide emission | ton               |

Note: (I, T, K): I is the intercept, T is the trend, L is the lag length, and N is none; * and ** denote the null hypothesis of a unit root rejected at the 10% and 5% significance levels, respectively.
### Table 4. Unit root test results for non-ferrous metal ore mining and processing.

| Series | (I, T, K) | ADF | 0.5 Critical Value | 0.1 Critical Value | Prob. * |
|--------|-----------|-----|--------------------|--------------------|---------|
| GIOV   | (N, N, 2) | 1.293183 | −1.977378 | −1.602074 | 0.9387 |
| COD    | (N, N, 0) | 0.593911 | −1.970978 | −1.603693 | 0.8312 |
| AN     | (I, T, 0) | −2.941565 | −3.119910 | −2.701103 | 0.0674 |
| ISW    | (N, N, 0) | 0.457459 | −1.970978 | −1.603693 | 0.7987 |
| SO₂    | (N, N, 0) | −0.775078 | −1.970978 | −0.1603683 | 0.3608 |
|        | (I, T, 1) | −3.737389 | −3.933364 | −3.420030 | 0.0653 |
|        | (I, N, 0) | −3.441553 | −3.144920 | −2.713751 | 0.0308 |
|        | (I, N, 0) | −6.981994 | −3.144920 | −2.713751 | 0.0001 |
|        | (I, N, 0) | −4.756370 | −3.144920 | −2.713751 | 0.0036 |
|        | (I, N, 0) | −3.335679 | −3.144920 | −2.713751 | 0.0366 |

**Note:** (I, T, K): I is the intercept, T is the trend, L is the lag length, and N is none; * and ** denote the null hypothesis of a unit root rejected at the 10% and 5% significance levels, respectively.

### Table 5. Unit root test results for ferrous metal ore mining and processing.

| Series | (I, T, K) | ADF | 0.5 Critical Value | 0.1 Critical Value | Prob. * |
|--------|-----------|-----|--------------------|--------------------|---------|
| GIOV   | (I, N, 1) | −3.317284 | −3.144920 | −2.713751 | 0.0377 |
| COD    | (I, T, 2) | −3.783048 | −3.933364 | −3.420030 | 0.0616 |
| AN     | (I, N, 0) | −2.945174 | −3.119910 | −2.701102 | 0.0670 |
| ISW    | (N, N, 0) | 0.180184 | −1.970978 | −1.603693 | 0.7222 |
| SO₂    | (N, N, 0) | −0.838323 | −1.970978 | −1.603693 | 0.3334 |
|        | (I, N, 0) | −5.608179 | −3.933364 | −3.420030 | 0.0055 |
|        | (I, N, 0) | −2.720846 | −3.144920 | −2.713751 | 0.0989 |
|        | (I, N, 0) | −4.190148 | −3.144920 | −2.713751 | 0.0090 |
|        | (I, N, 0) | −3.874464 | −3.144920 | −2.713751 | 0.0166 |
|        | (I, N, 0) | −3.310650 | −3.144920 | −2.713751 | 0.0381 |

**Note:** (I, T, K): I is the intercept, T is the trend, L is the lag length, and N is none; * and ** denote the null hypothesis of a unit root rejected at the 10% and 5% significance levels, respectively.

### Table 6. Unit root test results for non-metal ore mining and processing.

| Series | (I, T, K) | ADF | 0.5 Critical Value | 0.1 Critical Value | Prob. * |
|--------|-----------|-----|--------------------|--------------------|---------|
| GIOV   | (N, N, 1) | 0.664558 | −1.970428 | −1.602922 | 0.8452 |
| COD    | (N, N, 2) | −0.934667 | −1.977378 | −1.602074 | 0.2901 |
| AN     | (I, N, 0) | −5.086009 | −3.119910 | −2.701103 | 0.0018 |
| ISW    | (N, N, 0) | 0.600191 | −1.970978 | −1.603693 | 0.8326 |
| SO₂    | (N, N, 0) | −0.704130 | −1.970978 | −1.603693 | 0.3920 |
|        | (I, N, 0) | −2.894985 | −3.175352 | −2.728985 | 0.0074 |
|        | (I, N, 0) | −4.635655 | −3.175352 | −2.728985 | 0.0052 |
|        | (I, N, 0) | −5.388098 | −3.175352 | −2.728985 | 0.0017 |
|        | (I, N, 0) | −3.075061 | −3.144920 | −2.713751 | 0.0560 |
|        | (I, N, 0) | −3.137956 | −3.144920 | −2.713751 | 0.0306 |

**Note:** (I, T, K): I is the intercept, T is the trend, L is the lag length, and N is none; * and ** denote the null hypothesis of a unit root rejected at the 10% and 5% significance levels, respectively.

### 3.2. Johansen Co-integration Tests

Because most time series of economic variables are non-stationary, a differencing method is often used in building a reasonable VAR model to eliminate the non-stationary trend. However, the variables in the first-order difference equation often do not have direct economic significance. To solve this problem, Engle and Granger proposed the co-integration theory and methods to build a reasonable model for non-stationary series [58]. The theory suggests that some linear combination of economic
variables may be stationary, even though the variables are not stationary and call this stationary linear combination a co-integration equation.

The Johansen co-integration is a widely used multivariate con-integration method and it is based on the VAR model. In this paper, the trace statistic is used to determine whether there is a co-integration relationship. The results of the Johansen co-integration tests between the logarithm of gross of industrial output value (LGIOV), logarithm of chemical oxygen demand (LCOD), logarithm of ammonia nitrogen (LAN), logarithm of industrial SO$_2$ (LSO$_2$) and logarithm of industrial solid wastes (LISW) of all mining industries are presented in Tables 7–11. As is evident in these tables, all null hypotheses in which there is no co-integration equation are rejected and there are one or two equations between variables. Therefore, a co-integration relationship exists between the LGIOV and LCOD, LAN, LSO$_2$ and LISW in all mining industries.

**Table 7.** Johansen co-integration test for coal mining and washing.

| Hypothesized No. of CE(s) | Eigen Value | Trace Statistic | 0.1 Critical Value | Prob. ** |
|--------------------------|-------------|-----------------|-------------------|----------|
| AN                       | None *      | 0.575470        | 15.54843          | 13.42878 | 0.0491   |
|                          | At most 1 * | 0.355274        | 5.267164          | 2.705545 | 0.0217   |
| COD                      | None *      | 0.9222961       | 36.11994          | 13.42878 | 0.0000   |
|                          | At most 1 * | 0.360168        | 5.358602          | 2.705545 | 0.0206   |
| ISW                      | None *      | 0.613525        | 16.00155          | 13.42878 | 0.0419   |
|                          | At most 1 * | 0.318033        | 4.593290          | 2.705545 | 0.0321   |
| SO$_2$                   | None *      | 0.602425        | 14.56814          | 13.42878 | 0.0686   |
|                          | At most 1 * | 0.252962        | 3.499675          | 2.705545 | 0.0614   |

Note: * denotes the null hypothesis rejected at a 10% significance level; ** denotes the null hypothesis rejected at a 5% significance level.

**Table 8.** Johansen co-integration test for petroleum and natural gas extraction.

| Hypothesized No. of CE(s) | Eigen Value | Trace Statistic | 0.1 Critical Value | Prob. ** |
|--------------------------|-------------|-----------------|-------------------|----------|
| AN                       | None *      | 0.647262        | 14.29508          | 10.47457 | 0.0231   |
|                          | At most 1 * | 0.138627        | 1.790728          | 2.976163 | 0.2127   |
| COD                      | None *      | 0.578479        | 10.48204          | 10.47457 | 0.0997   |
|                          | At most 1 * | 0.009571        | 0.115407          | 2.976163 | 0.7797   |
| ISW                      | None *      | 0.490082        | 10.75556          | 10.47457 | 0.0902   |
|                          | At most 1 * | 0.199717        | 2.673485          | 2.976163 | 0.1206   |
| SO$_2$                   | None *      | 0.602425        | 14.58614          | 13.42878 | 0.0686   |
|                          | At most 1 * | 0.252962        | 3.499675          | 2.705545 | 0.0614   |

Note: * denotes the null hypothesis rejected at a 10% significance level; ** denotes the null hypothesis rejected at a 5% significance level.

**Table 9.** Johansen co-integration test for non-ferrous metal ore mining and processing.

| Hypothesized No. of CE(s) | Eigen Value | Trace Statistic | 0.1 Critical Value | Prob. ** |
|--------------------------|-------------|-----------------|-------------------|----------|
| AN                       | None *      | 0.684011        | 18.74787          | 13.42878 | 0.0156   |
|                          | At most 1 * | 0.336531        | 4.923283          | 2.705545 | 0.0265   |
| COD                      | None *      | 0.900634        | 31.84773          | 13.42878 | 0.0001   |
|                          | At most 1 * | 0.291803        | 4.140395          | 2.705545 | 0.0419   |
| ISW                      | None *      | 0.649359        | 16.83893          | 13.42878 | 0.0312   |
|                          | At most 1 * | 0.299003        | 4.263022          | 2.705545 | 0.0389   |
| SO$_2$                   | None *      | 0.665964        | 17.64016          | 13.42878 | 0.0234   |
|                          | At most 1 * | 0.311704        | 4.482436          | 2.705545 | 0.0342   |

Note: * denotes the null hypothesis rejected at a 10% significance level; ** denotes the null hypothesis rejected at a 5% significance level.
Table 10. Johansen co-integration test for ferrous metal ore mining and processing.

| Hypothesized No. of CE(s) | Eigen Value | Trace Statistic | 0.1 Critical Value | Prob. ** |
|---------------------------|-------------|-----------------|-------------------|---------|
| AN                        | None *      | 0.601836        | 17.78395          | 13.42878| 0.0222  |
|                           | At most 1 * | 0.429421        | 6.732350          | 2.705545| 0.0095  |
| COD                       | None *      | 0.680474        | 20.50181          | 13.42878| 0.0081  |
|                           | At most 1 * | 0.433096        | 6.810791          | 2.705545| 0.0091  |
| ISW                       | None *      | 0.676599        | 21.35281          | 13.42878| 0.0058  |
|                           | At most 1 * | 0.478235        | 7.806465          | 2.705545| 0.0052  |
| SO₂                       | None *      | 0.652966        | 17.30102          | 13.42878| 0.0265  |
|                           | At most 1 * | 0.318474        | 4.601048          | 2.705545| 0.0319  |

Note: * denotes the null hypothesis rejected at a 10% significance level; ** denotes the null hypothesis rejected at a 5% significance level.

Table 11. Johansen co-integration test for non-metal ore mining and processing.

| Hypothesized No. of CE(s) | Eigen Value | Trace Statistic | 0.1 Critical Value | Prob. ** |
|---------------------------|-------------|-----------------|-------------------|---------|
| AN                        | None *      | 0.744436        | 20.11470          | 17.98038| 0.0524  |
|                           | At most 1 * | 0.267975        | 3.743292          | 7.556722| 0.4517  |
| COD                       | None *      | 0.819147        | 26.47076          | 23.34234| 0.0421  |
|                           | At most 1 * | 0.399392        | 5.949903          | 10.66637| 0.4667  |
| ISW                       | None *      | 0.669033        | 19.57367          | 17.98038| 0.0620  |
|                           | At most 1 * | 0.406863        | 6.304840          | 7.556722| 0.1685  |
| SO₂                       | None *      | 0.811809        | 26.61353          | 23.34234| 0.0404  |
|                           | At most 1 * | 0.527215        | 8.240259          | 10.66637| 0.2327  |

Note: * denotes the null hypothesis rejected at a 10% significance level; ** denotes the null hypothesis rejected at a 5% significance level.

3.3. VAR Model

In this section, the VAR model is used to analyze the nexus between the industry development and the environmental pollution in every mining industry. The lag order is selection in Section 3.3.1. Section 3.3.2 presents the constructions and the stability tests of VAR model. Section 3.3.3 describes impulse response functions.

3.3.1. Optimal Lag Order Analysis

The longer the lag period is, the lower the degree of freedom and the weaker the explanatory power. Therefore, it is necessary to select an optimal lag period for the variables in the model to have a strong explanatory power. In this paper, a lag of 1 is selected as a result of the logarithmic likelihood ratio (LogL), AIC, SC, sequential modified LR test statistic (LR), FPE (final prediction error) and HQ (Hannan-Quinn) information criterion, as shown in Tables 12–16.

Table 12. Lag selection criteria for coal mining and washing.

| Lag | LogL        | LR       | FPE          | AIC          | SC        | HQ        |
|-----|-------------|----------|--------------|--------------|-----------|-----------|
| 0   | −4.898238   | NA       | 3.16 × 10⁻⁶  | 1.522806     | 1.740094  | 1.478143  |
| 1   | 52.35847    | 61.66107 | 3.22 × 10⁻⁸  | −3.439765 *  | −2.136036 | −3.707740 |

Note: * indicates lag order selected using the criterion.
Table 13. Lag selection criteria for petroleum and natural gas extraction.

| Lag | LogL   | LR     | FPE    | AIC    | SC     | HQ     |
|-----|--------|--------|--------|--------|--------|--------|
| 0   | −52.41949 | NA     | 0.004729 | 8.833768 | 9.051056 | 8.789105 |
| 1   | −0.133846 | 56.30762* | 0.000103* | 4.635976* | 5.939706* | 4.368001* |

Note: * indicates lag order selected using the criterion.

Table 14. Lag selection criteria for non-ferrous metal ore mining and processing.

| Lag | LogL   | LR     | FPE    | AIC    | SC     | HQ     |
|-----|--------|--------|--------|--------|--------|--------|
| 0   | −60.59859 | NA     | 0.016643 | 10.09209 | 10.30938 | 10.04743 |
| 1   | 10.35923 | 76.41612* | 2.06 × 10⁻⁵* | 3.021657* | 4.325386* | 2.753682* |

Note: * indicates lag order selected using the criterion.

Table 15. Lag selection criteria for ferrous metal ore mining and processing.

| Lag | LogL   | LR     | FPE    | AIC    | SC     | HQ     |
|-----|--------|--------|--------|--------|--------|--------|
| 0   | −70.28704 | NA     | 0.073885 | 11.58262 | 11.79991 | 11.53796 |
| 1   | −5.819538 | 69.42654* | 0.000248* | 5.510698* | 6.814427* | 5.242723* |

Note: * indicates lag order selected using the criterion.

Table 16. Lag selection criteria for non-metal ore mining and processing.

| Lag | LogL   | LR     | FPE    | AIC    | SC     | HQ     |
|-----|--------|--------|--------|--------|--------|--------|
| 0   | −64.54193 | NA     | 0.030528 | 10.69876 | 10.91605 | 10.65410 |
| 1   | 12.79631 | 83.28733* | 1.42 × 10⁻⁵* | 2.646722* | 3.950451* | 2.378747* |

Note: * indicates lag order selected using the criterion.

3.3.2. VAR Estimates and Stability Tests

Through the unit tests and the co-integration tests, we identified that all variables are stationary after first-order differencing and there is a co-integration relationship between LGIOV and the LCOD, LAN, LSO₂ and LISW in every mining industry. Therefore, the VAR model, which includes these variables, can be estimated using the AIC and SC criteria. The estimates and their t-values and standard errors are presented in Table 17.

It is necessary to test the stability of VAR model before use the mode to conduct impulse response. The characteristic roots of the coefficient matrix, pesaran and pesaran procedure are used in the stationary test. Figures 3–7 show that the characteristic roots of every mining industry are less than 1 and lie inside the unit circle. This indicates that the model satisfies the stability condition.

It can be seen from the above analysis, the results of unit-root tests and Johansen co-integration testes show that the variables is stationary. The reliability of the model estimation results depends on the stationariness of the variables. Meanwhile, the model has been proved to be stable and has a high degree of fit to the sample. Hence, the estimation results of data for 14 years is reliable.
Table 17. Vector autoregression estimates.

|                      | Coal Mining and Washing | Petroleum and Natural Gas Extraction | Non-Ferrous Metal Ore Mining and Processing | Ferrous Metal Ore Mining and Processing | Non-Metal Ore Mining and Processing |
|----------------------|-------------------------|--------------------------------------|--------------------------------------------|----------------------------------------|------------------------------------|
| **AN(−1)**           | 0.013800                | 0.173641                             | 0.010107                                   | 0.495835                               | 0.103729                           |
|                      | (0.13192)               | (0.18427)                            | (0.20466)                                  | (0.24020)                              | (0.09501)                           |
|                      | [0.10461]               | [0.94229]                            | [0.04938]                                  | [2.06422]                              | [1.09176]                           |
| **COD(−1)**          | −0.222574               | 0.085947                             | −0.419635                                  | 0.184019                               | −0.101893                          |
|                      | (0.18916)               | (0.15746)                            | (0.55758)                                  | (0.95134)                              | (0.21591)                           |
|                      | [−1.17663]              | [0.54583]                            | [−0.75262]                                 | [0.19343]                              | [−0.47193]                          |
| **GIOV(−1)**         | 0.911397                | 1.122400                             | 0.404800                                   | 0.207995                               | 0.240634                           |
|                      | (0.11579)               | (0.19102)                            | (0.25404)                                  | (0.13985)                              | (0.15037)                           |
|                      | [7.787093]              | [5.87582]                            | [1.59344]                                  | [1.48728]                              | [1.60033]                           |
| **ISW(−1)**          | −0.102868               | 0.059327                             | 0.123448                                   | 0.240839                               | 0.087564                           |
|                      | (0.08728)               | (0.05662)                            | (0.36974)                                  | (0.29701)                              | (0.33694)                           |
|                      | [−1.17859]              | [1.04860]                            | [0.33388]                                  | [0.81089]                              | [0.25988]                           |
| **SO₂(−1)**          | 0.056690                | 0.020648                             | 0.012060                                   | 0.039336                               | 0.032275                           |
|                      | (0.29353)               | (0.01346)                            | (0.03866)                                  | (0.03804)                              | (0.02164)                           |
|                      | [0.19313]               | [1.53439]                            | [0.31194]                                  | [1.03412]                              | [1.49160]                           |
| **C**                | 3.464985                | −3.327779                           | 9.051754                                   | 0.226979                               | 3.866749                           |
|                      | (4.28332)               | (3.43990)                            | (6.63006)                                  | (10.6432)                              | (2.67781)                           |
|                      | [0.80895]               | [−0.96741]                           | [1.36526]                                  | [0.02133]                              | [1.44400]                           |
| **R²**               | 0.991146                | 0.937076                             | 0.586858                                   | 0.697211                               | 0.745154                           |
| **Adj_R²**           | 0.984822                | 0.892131                             | 0.291756                                   | 0.480933                               | 0.563120                           |
| **SSR**              | 0.079826                | 0.113653                             | 0.976506                                   | 1.718965                               | 0.387413                           |
| **S.E. equation**    | 0.106788                | 0.127421                             | 0.373498                                   | 0.495547                               | 0.235255                           |
| **F-statistic**      | 156.7269                | 20.84919                             | 1.988653                                   | 3.223678                               | 4.093055                           |
| **LogL**             | 14.65733                | 12.36093                             | −1.619498                                  | −5.295226                              | 4.389867                           |
| **AIC**              | −1.331898               | −0.978605                            | 1.172230                                   | 1.737727                               | 0.247741                           |
| **SC**               | −1.071152               | −0.717899                            | 1.432979                                   | 1.998473                               | 0.508486                           |

Note: standard error is shown in parentheses, and t-statistics are in brackets.

Figure 3. VAR roots of characteristic polynomial of mining and washing of coal. Note: blue dots indicate characteristic roots.
oxygen demand, ammonia nitrogen and industrial solid wastes all show a negative response to industrial output value fluctuation; industrial SO2 shows a negative response in the short-term but subsequently achieve equilibrium prior to showing a positive response in the long-term; the ammonia nitrogen discharged shows a positive response, and the oxygen demand and industrial solid wastes show a negative response to industrial output value fluctuation in the short-term but fluctuation in the short-term but subsequently achieve equilibrium prior to showing a positive response in the long-term. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ± 2 standard deviations of the responses. As observed in Figure 9, in petroleum and natural gas extraction, the discharge of chemical pollutants charged to industrial output value of mining and washing of coal.

**Figure 4.** VAR roots of characteristic polynomial of extraction of petroleum and natural gas. Note: blue dots indicate characteristic roots.

**Figure 5.** VAR roots of characteristic polynomial of mining and processing of non-ferrous metal ores. Note: blue dots indicate characteristic roots.

**Figure 6.** VAR roots of characteristic polynomial of mining and processing of ferrous metal ores. Note: blue dots indicate characteristic roots.

**Figure 7.** VAR roots of characteristic polynomial of mining and processing of nonmetal ores. Note: blue dots indicate characteristic roots.
3.3.3. Impulse Response Functions

In this section, the impulse response functions are applied to build the nexus between industry development and environmental pollution by investigating the responses of the environmental pollution variables caused by the industrial output value shock in each mining industry. As observed in Figure 8, in the coal mining and washing industry, the discharge of chemical oxygen demand and industrial solid wastes show a negative response to industrial output value fluctuation in the short-term but subsequently achieve equilibrium prior to showing a positive response in the long-term; the ammonia nitrogen discharged shows a positive response, and the industrial SO$_2$ discharged shows a negative response.

![Figure 8](image)

**Figure 8.** Responses of pollutants charged to industrial output value of mining and washing of coal. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ±2 standard deviations of the responses.

As observed in Figure 9, in petroleum and natural gas extraction, the discharge of chemical oxygen demand, ammonia nitrogen and industrial solid wastes all show a negative response to industrial output value fluctuation; industrial SO$_2$ shows a negative response in the short-term but subsequently achieves equilibrium prior to showing a positive response in the long-term.

As observed in Figures 10–12, in non-ferrous metal ore, ferrous metal ore and non-metal ore mining and processing, the responses of every pollutant to industrial output value fluctuation are the same. Among them, the discharge of ammonia nitrogen, industrial SO$_2$ and industrial solid wastes all show a positive response to industrial output value fluctuation and chemical oxygen demand shows a negative response.
Figure 9. Responses of pollutants charged to industrial output value of extraction of petroleum and natural gas. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ± 2 standard deviations of the responses.

As observed in Figures 10–12, in non-ferrous metal ore, ferrous metal ore and non-metal ore mining and processing, the responses of every pollutant to industrial output value fluctuation are the same. Among them, the discharge of ammonia nitrogen, industrial SO2 and industrial solid wastes all show a positive response to industrial output value fluctuation and chemical oxygen demand shows a negative response.

Figure 10. Responses of pollutants charged to industrial output value of mining and processing of non-ferrous metal ores. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ± 2 standard deviations of the responses.
Figure 11. Responses of pollutants charged to industrial output value of mining and processing of ferrous metal ores. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ±2 standard deviations of the responses.

Figure 12. Responses of pollutants charged to industrial output value of mining and processing of nonmetal ores. The solid lines indicate the mean responses to a one standard deviation shock, while the dotted lines represent ±2 standard deviations of the responses.
4. Discussion

According to the above empirical results, we come to the conclusion that in terms of water pollution, the discharge of COD decreased in coal mining and washing in the short-term but increased in the long-term, whereas it increased in the other industries. The discharge of AN decreased only in petroleum and natural gas extraction and increased in the others. This phenomenon is due to the limiting effect of weak emission standards for mining wastewater and because AN was not used as an indicator for wastewater treatment until 2011 [59]. Although the maximum permissible discharge concentrations of COD and AN are clear in the Integrated Wastewater Discharge Standard [60], to which discharged mining wastewater refers, the following two deficiencies limit the effects of the standard. First, the Integrated Wastewater Discharge Standard is not specific to each industrial sector. The maximum permissible discharge concentrations in this standard are applied to the whole mining industry. The fact that the degree of pollution varies depending on different types of mineral resources has not been considered. Second, the maximum permissible discharge concentrations adopted in 1996 are too high to efficiently control the pollutants. However, COD has been taken as an indicator of sewage treatment in the China Environmental Protection plan, but AN was not used until 2011. Hence, the weak limiting effect of emission standards and the indicators for wastewater treatment that are not specific to each industrial sector caused a decrease in the COD in all types of mining industries (for coal mining and washing, it only decreased in the short-term), but the AN increased in most mining industries except for petroleum and natural gas extraction. The reason for the increase in COD from coal mining and washing in the long-term after decreasing in the short-term is that tactic of increasing production, which is adopted by most coal enterprises to compensate for losses caused by falling coal prices, leads to an increase in the COD discharged per gross industrial output value. The reason the AN only decreased in petroleum and natural gas extraction is that a great deal of industrial wastewater in which the COD is not treated is injected into the oil field. Furthermore, the injection rate is greater than 90%, and this rejected wastewater is not counted as discharged wastewater. Hence, the AN in petroleum and natural gas extraction decreased.

In terms of air pollution, the industrial SO\(_2\) decreased in coal mining and washing, decreased in the short term in petroleum and natural gas extraction, but increased in the long-term and increased in the other three mining industries. The reason for this phenomenon is that the effect of the Integrated Emission Standard of Air Pollutants, to which mining waste gas refers, is not strong due to the same deficiencies as in the Integrated Wastewater Discharge Standard [61]. However, the Discharge Standard for Coal Industry [62] lowered the maximum permissible discharge concentration of industrial SO\(_2\), causing the industrial SO\(_2\) to decrease in coal mining and washing. In addition, the comprehensive utilization of coal gangue decrease the industrial SO\(_2\) to some extent. A large number of coal gangue are produced and are piled up [63]. The coal gangue piles are prone to spontaneous combustion, which is hazardous to environment by discharge the harmful gas including sulfur dioxide. With the increasing awareness of environmental protection and comprehensive utilization of resources in China, the coal gangue is used for power generation and making bricks, etc. This change makes the gangue piles turned into man-made eco-park and decrease the amount of sulfur dioxide discharged [64,65]. The reason the industrial SO\(_2\) decreased in the short-term in petroleum and natural gas extraction is that the industrial SO\(_2\) is mainly produced from natural gas purification plant tail gas and policies were introduced to encourage enterprises to improve the recovery and utilization of industrial SO\(_2\) in the tail gas of these purification plants. Nevertheless, the costs of tail gas treatment and the maximum permissible discharge concentrations for the extraction of petroleum and natural gas are too high. To pursue economic benefits, tail gas treatment equipment is the optimal choice for enterprises. This caused the industrial SO\(_2\) increase in the long-term in petroleum and natural gas extraction.

In terms of solid pollution, the industrial solid waste discharged decreased in petroleum and natural gas extraction, decreased in coal mining and washing in the short-term but increased in the long-term and increased in the three other types of mining industries. This phenomenon occurs because some of the Chinese government’s policies to promote the comprehensive utilization ratio
of the industrial solid wastes were only implemented in coal mining and washing and petroleum and natural gas extraction. The comprehensive utilization of 17% of coal gangue is required [66], and a 100% resource utilization ratio of oily sludge is required [67]. Furthermore, the enterprises that sell the coal gangue or oily sludge they produce and those that yield products made of coal gangue or oily sludge can return 50% value-added tax [68]. These policies decreased the industrial solid waste in petroleum and natural gas extraction and in coal mining and washing in the short-term. However, the tactic of increasing production, which is adopted by most coal enterprises to compensate for losses caused by falling coal prices, caused the increase in industrial solid waste in the long-term. In addition to the above three points, the uniformity of the pollution control policies and standards reduce the effect of pollution prevention to some extent because there are diversities in the level of economic development, industrial structure, environmental carrying capacity, etc., among the provinces [69–71]. Firstly, although the uniform pollution control policies and standards are stipulated by the central government, the responsibilities of local governments are not clear for environment pollution, and further how such responsibilities are evaluated [72]. In order to economic development, local governments, especially who face difficulty in economic development, are inclined to neglect their responsibilities for protecting local environment, and finally make the effects of uniform pollution control policies and standards unobvious [73–75]. Worse still, local governments may reduce the collection of emission fees to protect the profits of local companies [76]. For example, the industrial structure of Shanxi Province is single due to heavily dependent on coal industry. When the coal prices are low, it is a challenge for Shanxi Province to solve environmental problems according to the uniform policies and standards. Secondly, the diversities of environment carrying capacities among provinces can make the different environmental disturbance caused by the same amount of pollution discharged [77–80]. Therefore, the implementation of the uniform pollution control policies and standards is not rational. It can destruct the environment in ecologically fragile regions due to the low pollutant control polices and standards, which are suitable for regions with high environment carrying capacities. For example, the forest coverage rate and rainfall are low in northwest China, in which most province are environmental fragile. The environment can be construct if these provinces implement the same pollution control policies and standards as other regions.

5. Conclusions

Using a time series from 2001 to 2014, this paper investigated the nexus between industry development and environmental pollution in coal mining and washing, petroleum and natural gas extraction and non-ferrous metal ore, ferrous metal ore and non-metal ore mining and processing in China, considering the dynamic changes within the VAR model. The results are as follows.

The pertinence of standards for the discharge of industrial wastewater and industrial waste gas is not strong and the maximum permissible discharge concentrations in these standards are too high. These two problems limit the effect of the standards in most mineral industries. Hence, to reduce the discharge of pollutants in industrial wastewater and waste gas, niche targeting standards for industrial wastewater and the waste gas should be adopted and the maximum permissible discharge concentrations in the standards should be lowered for different mining industries according to the characteristics of pollutants in each mining industry.

Tax reduction policies to promote the comprehensive utilization of industrial solid waste in coal mining and washing and petroleum and natural gas extraction are effective. However, these policies are not adopted in other mining industries. Hence, to reduce the discharge of industrial solid waste in non-ferrous metal ore, ferrous metal ore and non-metal ore mining and processing, the enterprises that sell the industrial solid waste they produce and those that yield products made of industrial solid waste can return a part of the value-added tax in these three mining industries.

The tactic of increasing production, used by many coal enterprises, led to increases in the COD and industrial solid waste discharged in the long-term in this industry. Hence, to manage the problem of overcapacity of coal enterprises, the production of coal enterprises should be controlled within
a reasonable range by the Chinese government. Policies should also be adopted to encourage coal enterprises to extend the industrial chain by developing the coal chemical and coal gasification industries, which can increase the added value of the product to compensate for losses caused by falling prices.

The current uniform pollution control policies and standards have a shortage that they do not consider the diversity among different provinces. The diversity can reduce the effect of pollution prevention. Hence, the different pollution control policies and standards should be stipulated according to the level of economic development, industrial structure, environmental carrying capacity, etc., among provinces. Appropriately raise pollution control polices and standards in environmental fragile regions. Meanwhile, responsibilities of local governments for environment pollution should be determined and the method should be stipulated to evaluate the responsibilities.

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