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Does industrial upgrading promote eco-efficiency? —A panel space estimation based on Chinese evidence

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ABSTRACT

Industrial upgrading plays a significant role in promoting eco-efficiency, but existing studies ignore this aspect. Using improved and comprehensive measures of eco-efficiency, we assess how industrial upgrading influences the eco-efficiency of a certain province with provincial panel data during the period 1998–2017. We find that industrial upgrading significantly promotes eco-efficiency and yields significantly positive spatial spillover effects. Our findings provide empirical evidence that the government should push forward industrial upgrading decisively, as well as strengthening inter-regional and central-provincial collaboration in promoting eco-efficiency.

1. Introduction

Countries worldwide are restructuring their economies, especially their industrial structures, to achieve sustainable development (Gao, 2012; Buzdugan and Tuselmann, 2018; Fessehaie and Morris, 2018). Emerging markets, however, has long been troubled with the classic dilemma: to choose economic growth or environmental protection? Although rapid industrialization does bring about massive economic gains, they come with environmental consequences, which not only exacerbated the environment but also harmed human health, thus impeding long-term sustainable growth of the society (Hochberg, 2017; Shi et al., 2017; Chen et al., 2018; Su et al., 2019; Wang et al., 2020). The concept of eco-efficiency is proposed by the World Business Council for Sustainable Development (WBCSD) in 1992. According to WBCSD, being eco-efficient is to create more economic value with less ecological impacts. Though a commonly agreed definition does not exist, most of the scholars consider eco-efficiency as a development strategy of increased intensity of economic output with reduced intensity of material input as well as environmental damages (Widheden and Ringström, 2007; Cabeza et al., 2015; Čuček et al., 2015; Peças et al., 2019).

An eco-efficient economy could reduce ecological damages to the minimum while maximizing economic efficiency. Generally, developed economies with advanced industries are more eco-efficient than emerging markets that are at the lower end of the global industrial chain. By industrial upgrading, an economy enhances its capability and efficiency in resource utilization, increasing economic gains with less material waste and pollutants output. Cleaner production in industries would then bring about more efficient economic growth, better environment, and more gains in social welfare. Thus, pushing forward industrial upgrading is a fundamental way for emerging markets to achieve higher eco-efficiency.

Nevertheless, the existing literature has not yet made an in-depth discussion on the correlation between eco-efficiency and industrial structure. Previous studies only adopted the ratio of capital to labor (e.g., Anteweiler et al. 2001; Cole and Elliott, 2003; He and Wang, 2012), or the proportion of manufacturing industry to GDP (e.g., Auty, 1997; Jänicke et al., 1997; Cole, 2000) to measure industrial structure. However, these methods only scratch the surface of the problems and might lead to biased estimations since the capital might be utilized in polluting industries, the manufacturing sectors might not necessarily be clean, and clean manufacturing industries might not be efficient. Therefore, it is of great theoretical and practical value to accurately identify industrial upgrading, and to probe into the underlying mechanism of correlation between industrial upgrading and promotion of eco-efficiency. The result will indicate whether industrial upgrading is an ideal approach for emerging markets to achieve rapid economic growth while not to damage the environment. China, as the largest emerging economy, has made tremendous efforts in balancing economic growth and

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environmental protection. It is also undergoing major industrial upgrading, making China an ideal case to study the environmental effect of industrial upgrading in emerging markets. Besides, considering Chinese government's solid efforts in promoting eco-efficiency, it would be necessary to conduct empirical studies on whether these efforts paid off or not.

To fill the research gap, in this paper, we collect the data of 30 provinces in China from 1998 to 2017 to examine the correlation between industrial upgrading and eco-efficiency (Table 1). The empirical results indicate that rationalization and supererogation of industrial structure significantly promote the eco-efficiency. After considering the effects of regional interaction, we find that industrial rationalization and supererogation improve not only the eco-efficiency locally but also those in neighboring provinces. The spatial spillover effect of industrial upgrading on the eco-efficiency in Chinese provinces is significantly positive.

The marginal contributions of our research are: (1) We evaluate the effect of industrial structural change on eco-efficiency, filling the gaps in the previous studies. (2) Our empirical results demonstrate that industrial upgrading is conducive to eco-efficiency. (3) We adopt the Global Principal Components Analysis (GPCA) model to construct a comprehensive measurement index of eco-efficiency, overcoming the problems caused by research bias or single selection of indicator. (4) We use industrial rationalization and supererogation as proxy for industrial upgrading, creating an indicator that is more persuasive compared to the indicators adopted by previous studies. (5) We consider the spatial spillover effect in the model, improving accuracy of the mechanism of how industrial structural change would affect eco-efficiency. Compared to the previous studies, we could attain more robust empirical results and precisely identify the correlation between industrial upgrading and eco-efficiency.

The rest of the paper is organized as follows. Section 2 gives a brief review on the current literature. Section 3 constructs the empirical model, followed by Section 4 which summarizes the dataset. Section 5 delves into the empirical results and data analysis. The last section deals with conclusion and policy implications.

Table 1
The 30 Chinese provinces in the sample.

Region	No.	Province
Eastern China	1	Beijing
	2	Fujian
	3	Guangdong
	4	Hainan
	5	Hebei
	6	Heilongjiang
	7	Jilin
	8	Jiangsu
	9	Liaoning
	10	Shandong
	11	Shanghai
	12	Tianjin
	13	Zhejiang
Central China	14	Anhui
	15	Henan
	16	Hubei
	17	Hunan
	18	Jiangxi
	19	Shanxi
Western China	20	Chongqing
	21	Gansu
	22	Guangxi
	23	Guizhou
	24	Inner Mongolia
	25	Ningxia
	26	Qinghai
	27	Shaanxi
	28	Sichuan
	29	Xinjiang
	30	Yunnan

2. Literature review

The correlation between industrial structure and eco-efficiency has received considerable attention in environmental economics. Previous research is mainly conducted from the following two perspectives.

On one hand, from industrial classification based on the intensity of factor input, scholars emphasized the influence of industrial transformation on the environment. The ratio of capital to labor is often used to measure the structural conditions of the economy to investigate its environmental pollution. Anteweiler et al. (2001) find that the composition effect has less influence on environmental pollution by country-specific experience data. Cole and Elliott (2003) carry out similar research and find that the composition effect's influence on pollution emission was minimal. He and Wang (2012) indicate that structural change in the intensity of factor inputs increases dust and sulfur dioxide (SO2) emissions but reduces nitrogen oxide (NO) emissions and significantly changes the shape of the pollution-income Environmental Kuznets Curve.

On the other hand, some scholars use the proportion of manufacturing industry to GDP or the proportion of clean and polluting industries in the whole industry to reflect the industrial structure change to investigate the environmental pollution further. Auty (1997) shows that the conversion of the proportional structure of industrial categories is an essential factor in water and air pollution and substantial waste emission in a specific region. Jänicke et al. (1997) and Cole (2000) conclude that industrial structure adjustment is beneficial to reducing the intensity of pollutants per unit GDP. Dinda (2004) verifies that the transformation of industrial structure to knowledge-intensive and technology-intensive industries and services would reduce pollution levels and improve the eco-efficiency. Brock and Taylor (2005) point out that industrial structure optimization and upgrading were conducive to improving production efficiency and technological progress in energy conservation and emission reduction. Lan et al. (2012) finds that within-sector technological solutions to emissions abatement play a more critical role than reorganizing supply structures. The latest literature tends to conclude that industrial structure optimization and upgrading, especially the improvement of production efficiency and technological level, is more likely to favor the eco-efficiency.

However, the previous literature falls short in the following aspects. First, previous literature has limited choices of indicators to measure eco-efficiency. Some scholars use pollution emissions as indicators, but different choices of pollution indicators lead to different conclusions. For example, Antweiler et al. (2001), Liu et al. (2018) used sulfur dioxide (SO2) emission as the indicator; Lan et al. (2012), Zhou et al. (2012), Tian et al. (2014), and Zhang et al. (2018) used carbon dioxide (CO2) emission as an indicator; Cole and Elliott (2003) and He and Wang (2012) used sulfur dioxide (SO2), nitrogen oxides (NO), and carbon dioxide (CO2) emissions as indicators; Brock and Taylor (2005) used industrial waste gas and industrial wastewater discharge as indicators. Amri (2017) demonstrates the positive effect of non-renewable energy on CO2 emission and an insignificant effect of renewable energy on environmental improvement in Algeria. Bekun et al. (2019) observe a feedback causality between natural resources rent and economic growth in the selected EU-16 countries. Alvarado et al. (2018) suggest that urbanization and energy consumption have positive effects on CO2 emissions. Yi et al. (2020) study the effects of heterogeneous technological progress on haze pollution in China, finding that neutral and labor-saving technological progress are conducive the haze pollution while the capital-saving one is insignificant. (Wesseh et al., 2020) find that economic growth does increase CO2 emission, and mitigation of CO2 would lead to colossal output and consumption costs. Using the data in Pakistan, Khan et al. (2019) and Khan et al. (2020) find that energy consumption and economic growth significantly increase the emission of CO2 both in the short run and the long run. However, it is not able to depict the eco-efficiency by measuring a single or several aspect of pollution emissions.

Second, previous studies only focus on a particular aspect of the industrial structure change, not only failing to consider the different effects of industrial rationalization and supererogation, but also missing out on the influence of industrial rationalization and supererogation[1] on the eco-efficiency (Tian et al., 2014; Chang, 2015; Li et al., 2017). Previous studies use indicators such as factor input density, percentage changes in clean and polluting industries. Although such indicators could reflect the direction of industrial restructure to some extent, they fail to capture the optimization and upgrading of the industrial structure. Moreover, scholars tend to classify industries into different categories, which could be a subjective process. As there is no unified criterion of industrial classification on a worldwide scale, and different scholars' categorization undermines the credibility and robustness of the studies. For example, polluting industries that were defined by Jänicke et al. (1997) are different from those by Cole (2000). Some scholars point out that industrial upgrading should be studied from two perspectives, i.e., industrial rationalization and supererogation (Zhou, 1992), but did not discuss the methods to measure them accurately.

Last, previous studies have not considered that eco-efficiency and industrial structural change are interconnected between regions (e.g., Huang et al., 2011; Chen et al., 2017; Liu et al., 2018; Zhu et al., 2019). However, many studies have demonstrated that industrial upgrading is spatially interconnected, which means that local industrial upgrading influence that of other areas, and vice versa (Brun et al., 2002; Ciccarelli and Fachin, 2017; Li et al., 2018; Wu et al., 2020). Similarly, environmental issues like PM2.5, CO2, and SO2 emissions are also spatially correlated due to the movement of air and water (Jerrett et al., 2005; Balado-Naves et al., 2018; Chu et al., 2018; Feng and Wang, 2020; Goel and Saunoris, 2020). It is theoretically and practically plausible that industrial upgrading in one region would affect the eco-efficiency of the other region, since it reduces the pollutants that could be transferred to other regions. Moreover, regional governments might learn and simulate policies implemented by neighboring regions, leading to a spatial spillover effects of policies (Case et al., 1993; Revelli, 2005; Holly et al., 2011). The spreading implementation of similar policies in several neighboring regions would enhance the spatial spillover effects. Thus, it is significant to study the spatial effects of eco-efficiency and industrial upgrading to gain a more comprehensive understanding to the problem.

To bridge these research gaps, our study builds a measuring system to estimate the eco-efficiency index by using the GPCA model. We then construct a baseline regression model and a spatial effect model to examine the local and spatial effects of industrial upgrading on eco-efficiency. We also carry out further examinations to test the robustness, to address the concern of endogeneity, to capture the heterogeneous effects, and to identify the mechanisms.

3. Methodology

3.1. Basic model

To investigate the influence of industrial upgrading on regional eco-efficiency, referring to the empirical panel model of Elliott and Wu (2008) that studies the influences of eco-efficiency, we set up a linear panel regression model that does not consider spatial interaction:

$$y_{it} = \alpha_0 + \tau I_{it} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \tag{1}$$

In equation (1), the dependent variable y_{it} represents the eco-efficiency index of the region i in the year t, while I_{it} is to measure the degree of industrial upgrading in a province (rationalization index and supererogation index). μ_i indicates the individual effect of the province, which can be set by fixed effect and random effect. $\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$ is a classical random disturbance term. x_{it} is a set of control variables that affect the dependent variables.

3.2. The model with spatial interaction

Model (1) is based on the Gauss-Markov hypothesis, which assumed that the variables are independent from each other, and the interaction mechanism between regions is ignored. This hypothesis is not consistent because there is a comprehensive and universal connection between economic units. Therefore, we add spatial weighted terms of the dependent variables and construct a spatial lag model (2) with panel data. After the spatial interaction factor enters, the model could depict the interaction mechanism between provinces during the process of industrial upgrading. Thus, the model has more economic significance.

$$y_{it} = \alpha_0 + \delta \sum_{j=1}^{N} \omega_{ij} y_{jt} + \tau_1 I_{it} + \tau_2 \sum_{j=1}^{N} \omega_{ij} I_{jt} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \tag{2}$$

First, y_{jt} is the value of the dependent variable in other provinces. ω_{ii} is a spatial weighted matrix and is a $N \times N$ symmetric matrix that is used to characterize the dependence and association of spatial individuals. Specifically, the diagonal element ω_{ii} of the spatial weight matrix ω is set to 0, and the non-diagonal element ω_{ii} represents the economic and social correlation between the provinces and the provinces in the spatial dimension. The coefficient is a measure of whether variables are "mutually promoting" or "mutually inhibiting" between provinces (Revelli, 2005; Miranda et al., 2017; Elhorst et al., 2018). For this paper, if δ is significantly positive, it means that the eco-efficiency between provinces and regions is "mutually promoting." If it is significantly negative, it is "mutually inhibiting." The cross-regional external effect of environmental pollution has been widely observed and recognized, so it is necessary to consider this feature in empirical regression.

Second, to explore the effects of industrial upgrading of other provinces on the eco-efficiency of a particular province, the spatial weighted term $\sum_{j=1}^{N}\omega_{ij}I_{jt}$ is added to I_{it} of equation (3). In economic terms, the adjustment of the industrial structure of one province may affect the eco-efficiency of other provinces. Since there are economic ties between various provinces, such as factor flows and commodity trade, the adjustment of the industrial structure of one province would influence the production and consumption activities of other provinces through the flow of factors and domestic trade, and thus affect their eco-efficiency. This interaction is spatially important and has long been ignored by previous studies.

For the selection of the spatial weighted matrix, we use two types of matrix for estimation. (1) Spatial weighted matrix based on geographical distance, $\omega_{ij} = 1/d_{ij}$[2] which means that if the geographical distance between the two provinces is longer, their mutual influence would be smaller. (2) K-Nearest Neighbor Spatial Matrix, with which the nearest K areas surrounding a given spatial unit are weighted as 1, while the others are weighted as 0; generally, K = 4 (Anselin, 2003). Because we examine the influence of industrial upgrading on eco-efficiency, it is rational to construct a spatial matrix from the geographic distance dimension. Besides, to reduce or eliminate the external influence between provinces, the weight matrix is standardized as $\omega_{ij}^* = \omega_{ij}/\sum_{j=1}^{N}\omega_{ij}$, so that the sum of the row elements is equal to 1.

3.3. Estimation method

Kelejian and Prucha (2002), Kelejian et al. (2006), and Lee and Yu

[1] Industrial rationalization and industrial supererogation are two dimensions to measure the quality of the industrial structure of an economy. Industrial rationalization refers to the optimal proportion between various industries while industrial supererogation refers to the ratio of gross value of the service sector to that of the manufacturing sector (Li et al., 2017; Wang et al., 2019; Zhao et al., 2020).

[2] d_{ij} refers to the distance between centroids of province i and province j.

(2010) combine the panel data model and the spatial lag model and propose a spatial lag model with fixed effect and random effect. A spatial lag model based on panel data with individual effect such as equation (2) could be represented as:

$$y_{it} = \delta \sum_{j=1}^{N} \omega_{ij} y_{jt} + \boldsymbol{x_{it}\beta} + \mu_i + \varepsilon_{it} \tag{3}$$

3.4. Spatial lag model with fixed effect

According to Anselin and Le Gallo (2006), if the independent variable of a spatial effect model with spatial lag is expanded, two problems emerge. First, the endogeneity of $\sum_j \omega_{ij} y_{jt}$ violates the assumption of the standard regression model $E[(\sum_{j=1}^{N} \omega_{ij} y_{it})\varepsilon_{it}] = 0$. In the estimation, the coherence must be considered. Second, the spatial dependence between different observations at each spatial point at a certain period affects the estimation of the fixed effects.

The derived ML estimator considers the endogeneity of $\sum_j \omega_{ij} y_{jt}$. Assume that the space-specific effects are fixed, then the log-likelihood function of (3) is:

$$\begin{aligned} \log L = & -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + T\log|I_N - \delta W| \\ & -\frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \delta\sum_{j=1}^{N}\omega_{ij}y_{jt} - x_{it}\beta - \mu_i\right)^2 \end{aligned} \tag{4}$$

The second term on the right is the Jacobian term obtained from the conversion of ε, which considers the endogeneity of $\sum_j \omega_{ij} y_{jt}$ (Anselin, 1988).

The partial derivative of the log-likelihood function for μ_i is:

$$\frac{\partial \log L}{\partial \mu_i} = \frac{1}{\sigma^2}\sum_{t=1}^{T}\left(y_{it} - \delta\sum_{j=1}^{N}\omega_{ij}y_{jt} - x_{it}\beta - \mu_i\right) = 0, i = 1, \dots, N \tag{5}$$

Solve the μ_i in equation (5), and there is:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - \delta\sum_{j=1}^{N}\omega_{ij}y_{jt} - x_{it}\beta\right), i = 1, \dots, N \tag{6}$$

Substituting the solution of μ_i into the log-likelihood function and there is the concentrated log-likelihood function for β, δ and σ^2:

$$\begin{aligned} \log L = & -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + T\log|I_N - \delta W| \\ & -\frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^{*} - \delta\left[\sum_{j=1}^{N}\omega_{ij}y_{jt}\right]^{*} - x_{it}^{*}\beta\right)^2 \end{aligned} \tag{7}$$

Note that, $y_{it}^{*} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it}, x_{it}^{*} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$ is a mean removal process.

Anselin and Hudak (1992) have demonstrated how to use the cross-sectional data and ML method to estimate the parameters β, δ, and σ^2 of the spatial lag model. Using an estimating program, the log-likelihood function for β and δ and σ^2 in equation (7) is maximized. The only difference is that cross-sectional data from N observations is expanded into panel data with $N \times T$ observations. The estimation process consists of the following steps:

First, the observations are stacked into a cross-section in the order of $t = 1, \dots, T$ to get a vector Y^{*} and $(I_T \otimes W)Y^{*}$ with $NT \times 1$, and a matrix X^{*} about the mean removal variable with $NT \times K$. Note that these calculations can only be performed once and must not store the diagonal matrix $(I_T \otimes W)$ of $NT \times NT$. For large data sets, this will significantly reduce the computational speed of the ML estimator.

Second, let b_0 and b_1 be the OLS estimators for the regressions of X^{*} that use Y^{*} and $(I_T \otimes W)Y^{*}$ respectively, while e_0^{*} and e_1^{*} are the corresponding residuals. Then the concentrated log-likelihood function is maximized to obtain the ML estimator of δ. This concentrated log-likelihood function is:

$$\log L = C - \frac{NT}{2}\log\left[\left(e_0^{*} - \delta e_1^{*}\right)^T\left(e_0^{*} - \delta e_1^{*}\right)\right] + T\log|I_N - \delta W| \tag{8}$$

where C is a constant term and does not depend on δ.

Third, given a numerical estimate of δ, the β sum estimator can be calculated:

$$\beta = b_0 - \delta b_1 = \left(X^{*T}X^{*}\right)^{-1}X^{*T}\left[Y^{*} - \delta(I_T \otimes W)Y^{*}\right] \tag{9}$$

$$\sigma^2 = \frac{1}{NT}\left(e_0^{*} - \delta e_1^{*}\right)^T\left(e_0^{*} - \delta e_1^{*}\right) \tag{10}$$

Last, the matrix of the progression function of parameters is computed for statistical inference (standard errors and t-values). The form of the matrix is as follows (because this matrix is symmetric, the diagonal elements can be ignored):

$$Asy.Var\left(\beta, \delta, \sigma^2\right) = \begin{bmatrix} \frac{X^{*T}X^{*}}{\sigma^2} & & \\ \frac{X^{*T}\left(I_T \otimes \widetilde{W}\right)X^{*}\beta}{\sigma^2} & T^{*}tr\left(\widetilde{W}\widetilde{W} + \widetilde{W}^T\widetilde{W}\right) + \frac{\beta^T X^{*T}\left(I_T \otimes \widetilde{W}^T\widetilde{W}\right)X^{*}\beta}{\sigma^2} & \\ 0 & \frac{T}{\sigma^2}tr\left(\widetilde{W}\right) & \frac{NT}{2\sigma^4} \end{bmatrix} \tag{11}$$

where $\widetilde{W} = W(I_N - \delta W)^{-1}$, and "$tr$" represents the trace of the matrix.

3.5. Spatial lag model with random effect

If the spatial effect is assumed to be random, the log-likelihood value of the model in (3) would be:

$$\begin{aligned} \log L = & -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + T\log|I_N - \delta W| \\ & +\frac{N}{2}\log\varphi^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^{\cdot} - \delta\left[\sum_{j=1}^{N}\omega_{ij}y_{jt}\right]^{\cdot} - x_{it}^{\cdot}\beta\right)^2 \end{aligned} \tag{12}$$

Then, $y_{it}^{\cdot} = y_{it} - (1 - \varphi)\frac{1}{T}\sum_{t=1}^{T} y_{it}, x_{it}^{\cdot} = x_{it} - (1 - \varphi)\frac{1}{T}\sum_{t=1}^{T} x_{it}$, which is precisely the same as the log-likelihood function of the spatial lag model with a fixed effect in equation (4).

If β, δ, and σ^2 are given, it is possible to estimate φ by maximizing the concentrated log-likelihood function of φ. The concentrated log-likelihood function is:

$$\log L = -\frac{NT}{2}\log\left[\left(e(\varphi)\right)^T e(\varphi)\right] + \frac{N}{2}\log\varphi^2 \tag{13}$$

The basic elements of $e(\varphi)$ is:

$$\begin{aligned} e(\varphi)_{it} = & y_{it} - (1 - \varphi)\frac{1}{T}\sum_{t=1}^{T} y_{it} - \delta\left[\sum_{j=1}^{N}\omega_{ij}y_{jt} - (1 - \varphi)\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N}\omega_{ij}y_{jt}\right] \\ & - \left[x_{it} - (1 - \varphi)\frac{1}{T}\sum_{t=1}^{T} x_{it}\right]\beta \end{aligned} \tag{14}$$

We can use iterators again. First, set the values of the parameters β, δ, and σ^2, then continue the iteration until convergence, and the parameter φ can be estimated. This procedure combines the estimation method for spatial lag model parameters with fixed effects and the estimation method for model parameters without spatial random effects.

The progression function matrix of the parameter is:

$$Asy.Var\left(\beta,\delta,\sigma^2\right) = \begin{bmatrix} \frac{X^{\cdot T}X^{\cdot}}{\sigma^2} & & \\ \frac{X^{\cdot T}\left(I_T \otimes \widetilde{W}\right)X^{\cdot}\beta}{\sigma^2} & T^* tr\left(\widetilde{W}\widetilde{W} + \widetilde{W}^T\widetilde{W}\right) + \frac{\beta^T X^{\cdot T}\left(I_T \otimes \widetilde{W}^T\widetilde{W}\right)X^{\cdot}\beta}{\sigma^2} & \\ 0 & -\frac{1}{\sigma^2}tr\left(\widetilde{W}\right) & -\frac{1}{\sigma^2}tr\left(\widetilde{W}\right) \\ 0 & -\frac{1}{\sigma^2}tr\left(\widetilde{W}\right) & \frac{-N}{\sigma^2}\ \frac{NT}{2\sigma^4} \end{bmatrix} \tag{15}$$

4. Data

4.1. Dependent variables (eco-efficiency)

The World Business Council for Sustainable Development defines eco-efficiency as "creating more goods and services using fewer resources, generating less waste and pollution" (WBCSD, 2000). Many scholars agree that being eco-efficient demand the society to do more with less input, considering not only the economic growth but also the environmental consequence (Cabeza et al., 2015; Čuček et al., 2015; Caiado et al., 2017; Peças et al., 2019). The concept has been commonly adopted to build indicators for measuring the sustainability of a region, an industry, or a company (Derwall et al., 2005; Yu et al., 2013; Gómez et al., 2018). Following the definition of WBCSD, we define eco-efficiency as the performance of a region in promoting economic growth while reducing environmental impacts.

There are several approaches to quantify eco-efficiency. The Data Envelopment Analysis (DEA) method is the most popular one. However, the DEA model has the limitation of small sample bias and is "often criticized for lacking a statistical basis" (Simar and Wilson, 1998). The results from the traditional DEA model are generally biased and inconsistent. Bootstrap method is required to correct the deviation for more accurate and robust results (Kneip et al., 2008). To address the weakness brought by the DEA model, we employ the Bootstrap-DEA method proposed by Wilson (2008) to measure the eco-efficiency of 30 provinces in China, which is a significant improvement compared to the traditional method.

We then construct a system that could accurately measure eco-efficiency (Table 2). The output of eco-efficiency should be the aggregation of the value of the products or services produced in a region. Therefore, we choose the gross domestic product (GDP) of the province to be the output indicator of the eco-efficiency analysis as most of the studies did (Kondo and Nakamura, 2005; Yu et al., 2013; Rashidi and Saen, 2015; Robaina-Alves et al., 2015; Rybaczewska-Błażejowska and Gierulski, 2018). For the input of eco-efficiency, we divide the indicators into two categories. Following conventional wisdom, we consider both desirable and undesirable inputs in the system (Korhonen and Luptacik, 2004; Ramli and Munisamy, 2015; Gómez et al., 2018). The first group contains four desirable factors: the employment scale, the capital stock, the area of arable land and urban construction land, and the forest coverage. The first three indicators represent the devotion of labor, capital, and land factor respectively in the system. When total factor productivity is given, the more input of economic factors, the higher the GDP output. The data of capital stock is updated and extended based on Zhang et al. (2004). Forest coverage refers to the input of environmentally friendly factors in the system because it is widely agreed that forest is one of the best environments for building biodiversity (Bruelheide et al., 2014). The second group of indicators is undesirable, containing urban water usage, energy consumption (Energy Consumption per unit GDP), sulfur dioxide (SO2) emission, solid waste discharge, wastewater discharge, and dust emission. Following Dyckhoff and Allen (2001) and Korhonen and Luptacik (2004), we classified these negative polluting indicators as "Undesirable Input" to the system. The smaller these indicators are, the better the eco-efficiency of the economy.

Table 2
Input and output indicators to measure eco-efficiency.

Category	Indicator	Unit	Direction
Input	Employment Scale	100 Million People	Desirable
	Capital Stock	100 Million CNY	
	Area of Arable Land	Thousand Acre	
	Area of Urban Construction Land	Thousand Acre	
	Forest Coverage	%	
	Urban Water Usage	10 Thousand Ton	Undesirable
	Energy Consumption per unit GDP	SCE/100 Million CNY	
	Sulfur Dioxide (SO2) Emission	Ton	
	Solid Waste Discharge	10 Thousand Ton	
	Wastewater Discharge	10 Thousand Ton	
	Dust Emission	Ton	
Output	GDP	100 Million CNY	–

Based on the system above, we employ Bootstrap-DEA to measure the eco-efficiency of Chinese provinces. First, for all decision elements $DMU\ (x_k, y_k)$, $k = 1, \ldots, n$, the efficiency score $\widehat{\theta}_k$ is calculated using the conventional DEA model. Second, for the efficiency scores $\widehat{\theta}_k$ $(k = 1, \ldots, n)$ of n decision elements calculated in the first step, we use the Bootstrap method to generate the n-row random efficiency values $\theta^*_{1b}, \ldots, \theta^*_{nb}$ (b is the Bootstrap iteration in the bth time). Third, we calculate the "pseudo-sample" (X^*_{kb}, Y_k), where $k = 1, \ldots, n$. Forth, we obtain a "pseudo-estimate" from each "pseudo-sample" by the DEA method $(k = 1, \ldots, n)$. Last, by repeating the above process from the first step to the fourth step for B times, we could have a series of efficiency values $\widehat{\theta}^*_{kb}$, where $b = 1, \ldots, B$.

Then, we have the estimated efficiency of the Bootstrap-DEA model after correcting the bias[3]:

$$\widetilde{\theta}_k = \widehat{\theta}_k - \widehat{Bias}\left(\widehat{\theta}_k\right) = 2\widehat{\theta}_k - B^{-1}\sum_{b=1}^{B}\left(\widehat{\theta}^*_{kb}\right) \tag{16}$$

Fig. 1 is a brief visualization of the provincial eco-efficiency in China. The measurement results of eco-efficiency are omitted due to limited space and could be reached by contact.

4.2. Independent variables

We use industrial rationalization and supererogation to proxy industrial upgrading. Industrial rationalization refers to the reallocation of production factors among various industries, as well as changes in the proportion of the output value of different sectors (Clark, 1967; Kuznets, 1957). Zhou (1992) is one of the first to systematically illustrate the industrial structure theory and classify it into two categories, which are industrial rationalization and industrial supererogation. It has been widely cited by scholars, such as Albala-Bertrand (2016), Mbate (2016) and Wang et al. (2019). Industrial rationalization refers to the degree of proportional balance and coordination between industries. Industrial supererogation means the evolution of the industrial structure from a lower level to an advanced one. The index of industrial rationalization (ia) and upgrading (ib) are the independent variables in this paper.

Traditionally, empirical research on this topic is in line with the

[3] In this paper, the number of iterations of the eco-efficiency Bootstrap-DEA model is set to 2000 times, the confidence interval is 95%, and the CCR constant returns to scale assumption is adopted. We also carry out sensitivity analysis to replace the estimated parameters of the eco-efficiency Bootstrap-DEA model. For example, the number of iterations is replaced by 1000, 3000, and 5000 in order; while confidence intervals are replaced with 90% and 99% respectively, the results are not significantly different. This shows that the robustness of eco-efficiency estimation based on Bootstrap-DEA model is strong.

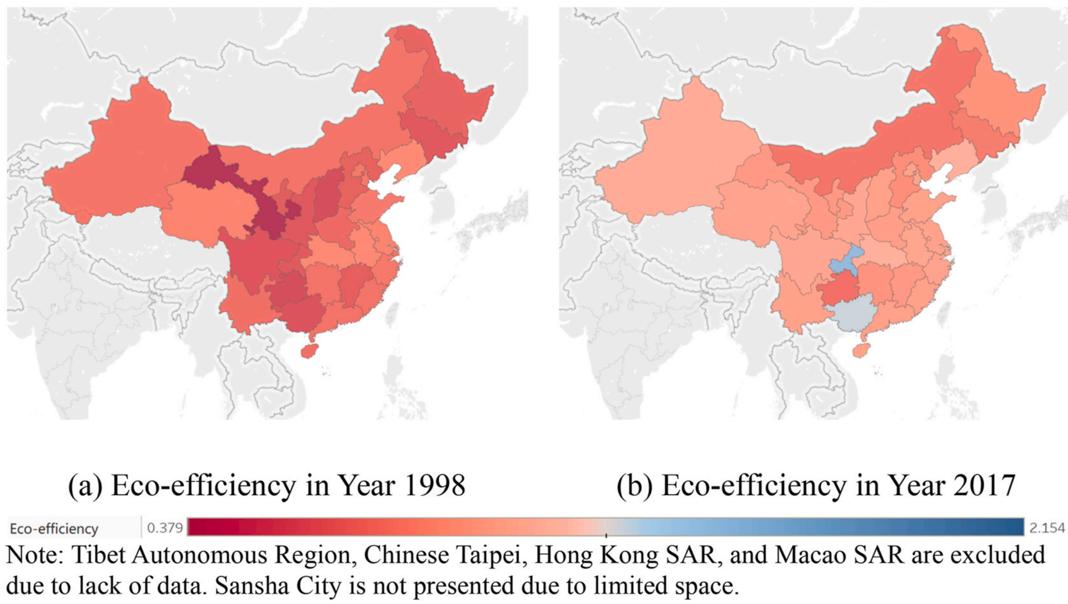

Fig. 1. The Eco-efficiency Index in China
Note: Tibet Autonomous Region, Chinese Taipei, Hong Kong SAR, and Macao SAR are excluded due to lack of data. Sansha City is not presented due to limited space.

resource allocation theory. They measure industrial rationalization based on the coupling degree between the input and output structures of factors, namely, industrial structure deviation degree: $E = \sum_{i=1}^{n}\left|\frac{Y_i/L_i}{Y/L} - 1\right| = \sum_{i=1}^{n}\left|\frac{Y_i/Y}{L_i/L} - 1\right|$, where Y represents output, L is the labor input, i is the industry sector of i, and n is the total number of industrial sectors. Based on the degree of deviation of the industrial structure, this paper proposes a new index $ia = 1/SR$ to measure industrial rationalization and let $SR = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)\left|\frac{Y_i/L_i}{Y/L} - 1\right|$, which not only maintains the advantages of industrial structure deviation but also reflects the importance of each industry through the weighted value of production. The smaller the value of *ia*, the more the economy deviates from the equilibrium, and the more unreasonable the industrial structure is, and vice versa.

Industrial supererogation reflects the change in the proportion of various industries and the increase in labor productivity. We set the index as. $ib = \sum_{i=1}^{n}(Y_{it}/Y_t)(LP_{it}/LP_{if})$[4] In this formula, Y_{it} represents the total output of i industry at the time of t; LP_{it}, the labor productivity of i industry at the time of t; LP_{if} is the labor productivity of i industry after the completion of industrialization, and n is the total number of industrial sectors. We choose the endpoint based on Chenery et al. (1986). For industries with high labor productivity, the higher the proportion of the industrial output value in the total output, the higher the level of industrial supererogation, and the higher the *ib* value.

Fig. 2 is a brief presentation of the measurement results of industrial upgrading. Details are omitted due to limited space and could be reached by contact. We take Yunnan Province (in western China) and Shanghai (in eastern China) as examples to better illustrate the process of industrial upgrading in China. Back in 1998, the ratio of the primary, secondary, and tertiary industry of Yunnan was 22: 44.7: 33.3, which had been adjusted to 14.3: 37.9: 47.8 in 2017. The labor productivity of Yunnan increased from 8006.7 CNY in 1998 to 54,209.8 CNY in 2017. For Shanghai, the trend is similar. The ratio of the primary, secondary, and tertiary industry of Shanghai was optimized from 1.9: 49.2: 48.8 in 1998 to 0.4: 30.5: 69.2 in 2017. The labor productivity of Shanghai increased from 47,816 CNY in 1998 to 223,200 CNY in 2017. The optimization of industrial structure, shifting from secondary industry toward tertiary industry, and dramatic increase of labor productivity are real evidence of industrial upgrading of Chinese provinces in the last two decades.

4.3. Control variables

The control variables are listed as follows. (1) Income is proxied by the logarithm of per capita GDP (*ly*) and the square term of the logarithm of per capita GDP (*ly2*). Income is the most basic economic variable and is the core variable in the Kuznets Inverted U curve proposed by Grossman and Krueger (1991). (2) Economic structure. Most scholars believe that the structure of the economy directly influences the environmental quality (Copeland and Taylor, 2004). In this paper, we define the structure to be the proportion of secondary industry (*wg2*), energy structure (*res*), urbanization rate (*cir*), and external dependence (*open*). The proportion of the secondary industry is represented by the proportion of industrial output in each province. The proportion of coal consumption in each region to the total energy consumption is used to measure the energy structure. The urbanization rate is indicated by the proportion of the urban population in each province to the total population. The external dependency is measured by the proportion of total imports and export in each region to GDP. (3) Institution, including environmental regulation intensity and environmental awareness. Environmental regulation intensity (*reg*) is represented by the proportion of sewage charges collected to the scale of GDP (Levinson, 1996). Environmental awareness (*pey*) is measured by the average educational attainment of every province. (4) Foreign capital. In this paper, the logarithm value of the actual amount of foreign capital (*lfdi*) is adopted to represent the factor because FDI is often used to verify the hypothesis of "Pollution Haven" in China.

The data are sourced from the *Compilation of Statistics Data of the People's Republic of China for the Past 60 Years*, *China Statistics Yearbook* of previous years, statistics yearbooks and statistical bulletins of various

[4] The improved supererogation index can identify the industrialization process of a country at different times, and it also addresses the dimensional issues. While capturing the changes in the proportion of industries, it also shows changes in industrial productivity.

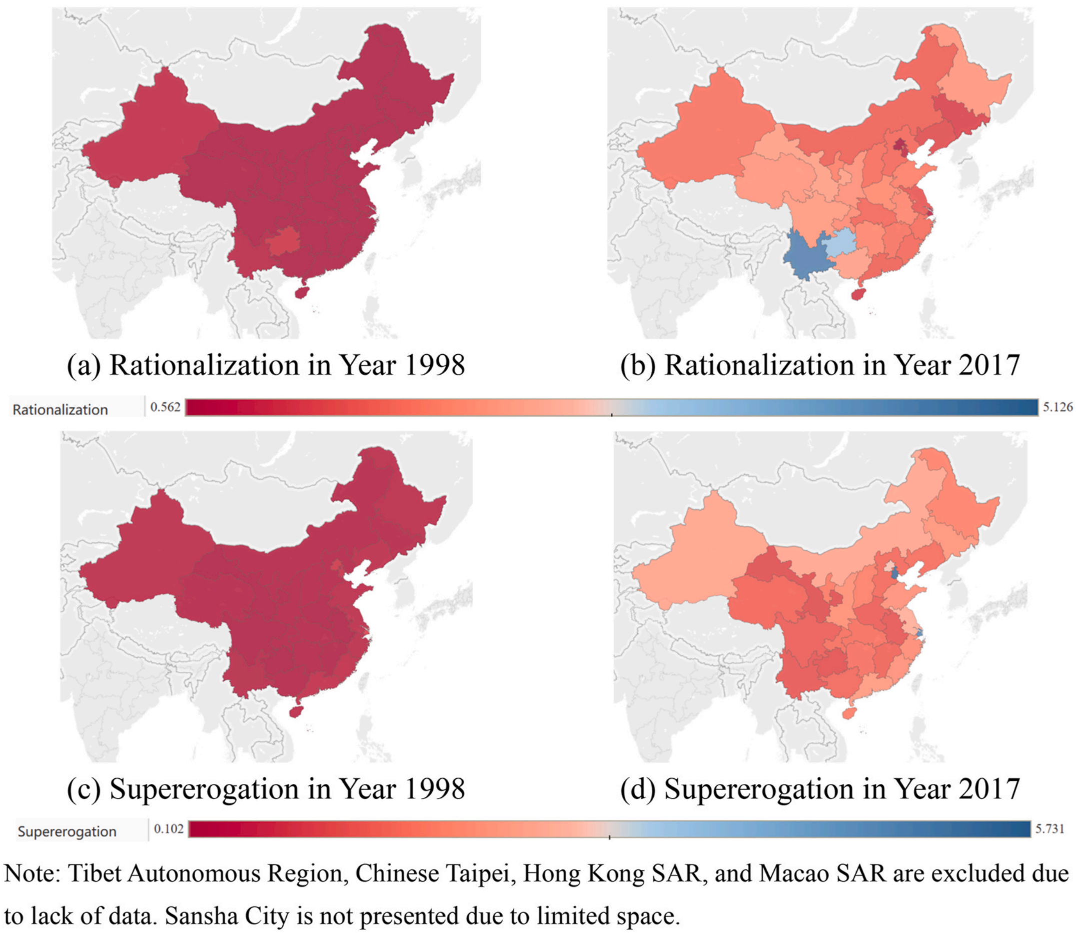

Fig. 2. Industrial Rationalization and Supererogation Index in China
Note: Tibet Autonomous Region, Chinese Taipei, Hong Kong SAR, and Macao SAR are excluded due to lack of data. Sansha City is not presented due to limited space.

provinces and cities, *China Environmental Yearbook, China Environmental Statistics Yearbook, China Energy Statistics Yearbook, China Labor Statistics Yearbook* and *China Population and Employment Statistics Yearbook*.[5] All the currency terms are adjusted according to the exchange rate of each year and the constant price in the year 2005.

5. Empirical results

5.1. Stationarity test

We take the stationarity test to confirm that the core variables could enter the regression. Table 3 presents the one-period lag stationarity test results by Levin-Lin-Chu test. The original hypothesis of the Levin-Lin-Chu test is that the variable has a unit root. The results suggest that the p-value of the three core variables reject the original hypothesis at least at the 10% level, which means that they are stationary.

Table 3
Stationarity test.

Variable	LLC Test (p-value)	Status
Eco-efficiency (*btr*)	0.0000***	stationary
Industrial Rationalization (*ia*)	0.0764*	stationary
Industrial Supererogation (*ib*)	0.0019***	stationary

5.2. Baseline regression results

Table 4 presents the results of the baseline regression. Independent variables are industrial rationalization *ia* (columns 1 to 4) and industrial supererogation *ib* (columns 5 to 8). We find that:

Industrial rationalization has significantly improved eco-efficiency. Columns 1 and 2 of Table 4 adopt the fixed-effect model. Columns 3 and 4 adopt the random-effect model. Columns 1 and 3 do not include any control variables, and the Hausman test shows that it is more appropriate to adopt a fixed-effect model. The coefficients are positive and at least significant at the 0.05 level. The coefficient of column 1 is 0.036, indicating that when industrial rationalization (*ia*) increases by one standard deviation, the eco-efficiency would increase by 0.93 standard deviations.[6] Columns 2 and 4 add control variables based on columns 1 and 3, respectively. The result is similar to that of columns 1 and 3. The Hausman test also shows that it is more appropriate to adopt a Fixed-effect model. The coefficients of the two columns of the industrial rationalization indexes are significantly positive.

Industrial supererogation has considerably improved eco-efficiency. Columns 5 to 8 of Table 4 are the results of the effects of industrial

[5] Based on the availability and statistical consistency, the sample is panel data of 30 provinces except Chinese Taipei, Hong Kong SAR, and Macao SAR in 1998–2017. Besides, the 2017 data of some of the variables could only be retrieved on related government websites.

[6] In this sample, the standard deviation of the industrial structure rationalization index is 3.79, while that of eco-efficiency index is 0.15.

Table 4
Baseline regression results.

Variable	Fixed effect		Random effect		Fixed effect		Random effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ia	0.036***	0.019**	0.030***	0.025***				
	(0.008)	(0.009)	(0.008)	(0.008)				
ib					0.168***	0.102***	0.138***	0.086**
					(0.037)	(0.036)	(0.035)	(0.036)
ly	0.228	0.447**	0.191	0.454**	0.471*	0.684***	0.384	0.538**
	(0.218)	(0.216)	(0.215)	(0.218)	(0.246)	(0.244)	(0.240)	(0.242)
ly2	−0.007	−0.020*	−0.005	−0.020*	−0.022*	−0.034***	−0.017	−0.025*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.013)
wg2		−0.000		−0.000		−0.000		−0.000
		(0.001)		(0.001)		(0.001)		(0.001)
reg		−0.002**		−0.003***		−0.003**		−0.003***
		(0.001)		(0.001)		(0.001)		(0.001)
pey		0.054***		0.035***		0.051***		0.032***
		(0.007)		(0.006)		(0.007)		(0.006)
lfdi		−0.006		−0.004		−0.006		−0.002
		(0.004)		(0.003)		(0.004)		(0.004)
open		0.000		−0.000***		0.000		−0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
cir		−0.002		−0.014		0.021		0.009
		(0.032)		(0.031)		(0.031)		(0.030)
res		0.003		0.000		−0.003		−0.007
		(0.018)		(0.015)		(0.018)		(0.015)
Constant	−0.756	−1.943*	−0.585	−1.908*	−1.758	−2.959**	−1.380	−2.228*
	(1.050)	(1.037)	(1.041)	(1.049)	(1.160)	(1.150)	(1.135)	(1.140)
Hausman	–	–	20.56***	50.05***	–	–	20.40***	73.88***
r^2	0.617	0.667	–	–	0.618	0.669	–	–
N	600	600	600	600	600	600	600	600

Note: ***, **, * represent the significance intervals of 1%, 5%, and 10%; The brackets are standard errors; *R2 stands for goodness of fit.* Same as below.

supererogation (*ib*) on eco-efficiency. Likewise, columns 5 and 6 are the analysis of the fixed-effect model and columns 7 and 8 of the random-effect model. The Hausman test shows that it would be more reasonable to use the fixed-effect model in the 5th and the 7th columns. The coefficients of industrial supererogation (*ib*) are all positive and significant at the 1% level. In columns 6 and 8, after control variables enter, the Hausman test agrees that it would be better to use the fixed-effect model, and the coefficients of the industrial supererogation (*ib*) are also positive and significant at the 1% level.

5.3. Empirical results considering spatial interaction effects

We further use the spatial lag model with fixed and random effects to examine the spatial effects of industrial rationalization and supererogation on eco-efficiency.

5.3.1. Spatial effect of industrial rantionalization on eco-efficienc

The dependent variable in Table 5 is eco-efficiency (*btr*), and the independent variable is industrial rationalization (*ia*). The spatial weight matrix is the geographical distance-weighted matrix (*wd*). Column 1 to 3 are the empirical results of the fixed-effect spatial lag model, and column 4 to 6 are the results of the random-effect spatial lag model.

The empirical results show that industrial rationalization does enhance the spatial effect of eco-efficiency. First, there is a positive spatial spillover effect of eco-efficiency (*Wbtr*). According to the result of column 1 to 3 of the fixed-effect model and column 4 to 6 of the random-effect model in Table 5, the coefficients of the spatial weight term of eco-efficiency (*Wbtr*) for both models are positive and significant at 1%. This indicates that there is a positive spillover effect of eco-efficiency of Chinese provinces. The coefficient of *Wbtr* in column 6 is 0.642, which means that if the eco-efficiency of other relevant provinces increases by one standard deviation, the eco-efficiency of a particular province will increase by 0.642 standard deviations.

Industrial rationalization of a province could significantly improve the eco-efficiency of its own and that of neighboring provinces. In column 1 to 3 (fixed-effect) and column 4 to 6 (random-effect) in Table 5, the coefficients of industrial rationalization (*ia*) is positive and significant on the 0.05 level, which again verifies that local industrial rationalization could significantly improve the eco-efficiency of neighboring provinces in China. The coefficient of the newly added spatial weight term (*Wia*) of industrial rationalization is positive and is at least statistically significant at 5% in columns 3 and 6. This shows that the influence of industrial rationalization on eco-efficiency is also reflected in the interaction between provinces.

Table 5 also indicates the direct and indirect effects of industrial rationalization on the eco-efficiency of Chinese provinces. According to LeSage and Pace (2009), and Vega and Elhorst (2013),[7] industrial rationalization of a region could both significantly improve the eco-efficiency of themselves and neighboring areas.

5.3.2. Spatial effect of industrial supererogation on eco-efficiency

Table 6 reveals the effects of industrial supererogation on eco-efficiency. The independent variable is industrial supererogation (*ib*). The spatial weight matrix is the geographical distance-weighted matrix (*wd*). Similarly, columns 1 to 3 are the results of the fixed-effect spatial lag model, and columns 4 to 6 are the empirical results of the random-effect spatial lag model.

There is a positive spatial spillover effect of industrial supererogation on eco-efficiency at the provincial level in China. The coefficients of the spatial weight term of eco-efficiency (*Wbtr*) are all significantly positive at the 1% level, which again verifies the existence of the positive spatial spillover effects of eco-efficiency.

The results of columns 1 to 6 in Table 6 show that the coefficients of industrial supererogation (*ib*) estimated by fixed-effect and random-effect models are significantly positive at 1%. This verifies that the industrial supererogation of a province can significantly improve its eco-efficiency. Moreover, the coefficients of the spatial weight term of the

[7] Numerically, the direct effect is the partial derivative of E[Y] versus X, the main diagonal element of its partial derivative matrix, and the non-diagonal element represents the indirect effect.

Table 5
Spatial effect of industrial rationalization on eco-efficiency.

Variable	Fixed-effect			Random-effect		
	(1)	(2)	(3)	(4)	(5)	(6)
Wbtr	0.738***	0.666***	0.654***	0.726***	0.649***	0.642***
	(0.040)	(0.049)	(0.051)	(0.041)	(0.051)	(0.051)
ia	0.025***	0.017**	0.020***	0.024***	0.017**	0.020***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Wia		0.038***	0.042***		0.035***	0.041***
		(0.010)	(0.014)		(0.010)	(0.012)
ly	0.498***	0.507***	0.565***	0.485***	0.497***	0.538***
	(0.176)	(0.175)	(0.182)	(0.178)	(0.177)	(0.184)
ly2	−0.025***	−0.026***	−0.030***	−0.024***	−0.026***	−0.028***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
wg2			0.001*			0.001**
			(0.001)			(0.001)
reg			−0.001			−0.001
			(0.001)			(0.001)
pey			0.012*			0.010*
			(0.007)			(0.006)
lfdi			−0.010***			−0.007**
			(0.004)			(0.003)
open			0.000			0.000
			(0.000)			(0.000)
cir			−0.038			−0.043
			(0.027)			(0.027)
res			−0.000			−0.007
			(0.016)			(0.013)
Constant				−2.221***	−2.168**	−2.330***
				(0.861)	(0.859)	(0.888)
Hausman				−10.58	24.72***	−82.92
r2	0.581	0.583	0.588	0.584	0.590	0.606
N	600	600	600	600	600	600
ia effect						
Direct effect	0.027***	0.021***	0.024***	0.026***	0.021***	0.024***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Indirect effect	0.070***	0.145***	0.153***	0.063***	0.129***	0.144***
	(0.023)	(0.032)	(0.044)	(0.020)	(0.028)	(0.037)
Total effect	0.098***	0.166***	0.177***	0.089***	0.150***	0.168***
	(0.028)	(0.034)	(0.047)	(0.025)	(0.030)	(0.040)

industrial supererogation (*Wib*) are all significantly positive at 1%, indicating that local industrial supererogation significantly affects that of neighboring provinces.

5.4. Robustness test

5.4.1. Considering the general equilibrium effect

Table 7 presents the results of the spatial effect model that both rationalization and supererogation enter. Columns 1 and 5 are results with the addition of industrial rationalization and supererogation but without their spatial weight terms. The coefficients of industrial rationalization (*ia*) and supererogation (*ib*) are both significantly positive at 5%. Columns 4 and 8 show the results after the spatial weight term of industrial rationalization and supererogation enter. The coefficients of rationalization (*ia*) and supererogation (*ib*) are still positively significant at 5%; the spatial weight term of industrial rationalization (*Wia*) and the spatial weight term of industrial supererogation (*Wib*) are also significantly positive. The promoting effects of local industrial upgrading on the eco-efficiency of other provinces do exist.

5.4.2. Changing the spatial weighted matrix

Table 8 reveals the results after changing the spatial weight matrix. We follow the method shown in columns 3 and 6 of Tables 4 and 5 and change the spatial weighted matrix from geographical distance weighted matrix (*wd*) to K-Nearest Neighbor Spatial Matrix (*wk*, K = 4) to carry out the robustness test. The results show that the coefficient of the spatial weight term of eco-efficiency (*Wbtr*) is significantly positive. The coefficients of industrial rationalization (*ia*) and industrial supererogation (*ib*) are all significantly positive. The coefficients of the spatial weight term of industrial rationalization (*Wia*) and industrial supererogation (*Wib*) are also significantly positive.

5.4.3. Considering the truncation problem

To avoid the truncation problem brought by the DEA method, we use the Tobit model to test the robustness.

Table 9 presents the empirical results. Columns 1 and 2 explore the effect of industrial rationalization (*ia*). The coefficients of the two columns are all significantly positive at the 1% level, confirming that industrial rationalization does promote eco-efficiency. Besides, the coefficient of the spatial weight term (*Wia*) is significantly positive at the 10% level, suggesting that the effects of industrial rationalization on eco-efficiency is embedded in the interaction between provinces in China. Columns 3 and 4 explore the effects of industrial supererogation (*ib*). The coefficients of the two columns are all significantly positive at the 1% level, revealing that industrial supererogation does promote eco-efficiency. The spatial weight term of industrial supererogation (*Wib*) is significantly positive at the 5% level, indicating that the influence of industrial supererogation on eco-efficiency is reflected in the interaction between Chinese provinces. In the meantime, the coefficients of the spatial weight term of eco-efficiency (*Wbtr*) are all positive and statistically significant at 1%. This indicates that there is a positive spillover effect of the eco-efficiency of Chinese provinces. The results are in line with those in the previous regressions, which means that after considering the truncation problem using the Tobit model, the previous conclusions stand.

Table 6
Spatial effect of industrial supererogation on eco-efficiency.

Variable	Fixed-effect			Random-effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Wbtr	0.737***	0.633***	0.614***	0.725***	0.621***	0.607***
	(0.040)	(0.052)	(0.054)	(0.041)	(0.054)	(0.055)
ib	0.119***	0.087***	0.079**	0.109***	0.087***	0.080***
	(0.030)	(0.031)	(0.031)	(0.029)	(0.030)	(0.031)
Wib		0.118***	0.136***		0.102***	0.130***
		(0.026)	(0.033)		(0.025)	(0.030)
ly	0.676***	0.676***	0.717***	0.637***	0.647***	0.664***
	(0.198)	(0.196)	(0.206)	(0.199)	(0.198)	(0.205)
ly2	−0.036***	−0.037***	−0.039***	−0.034***	−0.035***	−0.037***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
wg2			0.001			0.001*
			(0.001)			(0.001)
reg			−0.001			−0.002*
			(0.001)			(0.001)
pey			0.010			0.007
			(0.007)			(0.006)
lfdi			−0.011***			−0.006*
			(0.004)			(0.003)
open			0.000*			0.000**
			(0.000)			(0.000)
cir			−0.000			−0.000
			(0.000)			(0.000)
res			−0.001			−0.010
			(0.016)			(0.014)
Constant				−2.846***	−2.747***	−2.779***
				(0.941)	(0.936)	(0.969)
Hausman	–	–	–	−22.08	26.18***	−12.17
r2	0.587	0.585	0.586	0.590	0.594	0.617
N	600	600	600	600	600	600
ib effect						
Direct effect	0.129***	0.099***	0.091***	0.118***	0.098***	0.092***
	(0.027)	(0.027)	(0.028)	(0.027)	(0.026)	(0.027)
Indirect effect	0.331***	0.468***	0.461***	0.287***	0.408***	0.440***
	(0.105)	(0.089)	(0.104)	(0.088)	(0.077)	(0.094)
Total effect	0.460***	0.568***	0.553***	0.405***	0.506***	0.531***
	(0.125)	(0.104)	(0.119)	(0.109)	(0.092)	(0.110)

Table 7
Robustness test: Considering general equilibrium effect.

Variable	Fixed-effect				Random-effect			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wbtr	0.690***	0.661***	0.620***	0.615***	0.703***	0.652***	0.613***	0.610***
	(0.047)	(0.050)	(0.054)	(0.054)	(0.045)	(0.050)	(0.054)	(0.054)
ia	0.031***	0.028***	0.034***	0.037***	0.033***	0.029***	0.033***	0.036***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Wia		0.039***		0.030		0.039***		0.024
		(0.013)		(0.023)		(0.012)		(0.023)
ib	0.131***	0.126***	0.111***	0.107***	0.134***	0.131***	0.118***	0.114***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)
Wib			0.147***	0.207***			0.129***	0.180***
			(0.033)	(0.056)			(0.029)	(0.057)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman					1.02	52.03***	−110.50	−126.22
r2	0.578	0.597	0.601	0.603	0.603	0.615	0.627	0.627
N	600	600	600	600	600	600	600	600

5.5. Test of endogeneity

To address endogeneity, which might be that the improvement of eco-efficiency reversely affects industrial upgrading, we take two approaches. First, based on the logic that "the future could not affect the past", we use the lagged term of industrial rationalization and supererogation in the empirical test. Second, we use the lagged term of industrial rationalization and supererogation to be the instrumental variables in the IV-2SLS estimation. The results are shown in Table 10.

Columns 1 and 2 reveal the results of the first approach. The coefficients of the lagged term of industrial rationalization (*L.ia*) and industrial supererogation (*L.ib*) are significantly positive, at least at the 10% level. Besides, the lagged spatial weight term of industrial rationalization (*L.Wia*) and industrial supererogation (*L.Wib*) are significantly positive, at least at the 5% level, indicating that the upgrading of industries in a province would promote the eco-efficiency in other provinces. Moreover, the spatial weight term of eco-efficiency (*Wbtr*) is significantly positive at the 1% level, suggesting a positive spillover effect on the eco-efficiency in Chinese provinces.

Columns 3 and 4 present the results of the second approach. Both

Table 8
Robustness Test: Changing the Spatial Weighted Matrix (Using K-Nearest Neighbor Spatial Matrix *wk*).

Variable	Fixed-effect				Random-effect			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wbtr	0.348***	0.334***	0.341***	0.288***	0.368***	0.336***	0.368***	0.305***
	(0.048)	(0.049)	(0.047)	(0.050)	(0.047)	(0.049)	(0.047)	(0.050)
ia	0.027***	0.024***			0.029***	0.021**		
	(0.008)	(0.009)			(0.008)	(0.009)		
Wia		0.014				0.026***		
		(0.010)				(0.010)		
ib			0.121***	0.099***			0.115***	0.091***
			(0.034)	(0.034)			(0.034)	(0.034)
Wib				0.109***				0.115***
				(0.029)				(0.027)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman	–	–	–	–	−39.56	20.75**	45.78***	−8.39
r2	–	–	0.475	0.511	–	–	0.542	0.560
N	–	–	600	600	–	–	600	600

Table 9
Robustness test: Using Tobit model to address the truncation problem.

Variable	(1)	(2)	(3)	(4)
Wbtr		0.862***		0.823***
		(0.068)		(0.072)
Ia	0.023***	0.022***		
	(0.009)	(0.007)		
Wia		0.024*		
		(0.012)		
Ib			0.093***	0.088***
			(0.035)	(0.030)
Wib				0.080**
				(0.032)
Constant	−1.937*	−2.621***	−2.571**	−3.121***
	(1.023)	(0.882)	(1.126)	(0.965)
Control Variables	Yes	Yes	Yes	Yes
Ll	783.37	878.98	783.31	880.08
N	600	600	600	600

Table 10
Test of endogeneity.

Variable	(1)	(2)		(3)	(4)
Wbtr	0.673***	0.571***	*Wbtr*	0.673***	0.571***
	(0.050)	(0.060)		(0.050)	(0.060)
L.ia	0.018**		*ia*	0.018**	
	(0.008)			(0.008)	
L.Wia	0.028**		*Wia*	0.027**	
	(0.014)			(0.014)	
L.ib		0.037*	*ib*		0.036*
		(0.020)			(0.020)
L.Wib		0.159***	*Wib*		0.158***
		(0.038)			(0.037)
Control Variables	Yes	Yes	Control Variables	Yes	Yes
ll	862.55	868.81	ll	862.55	868.81
R2	0.561	0.599	R2	0.561	0.599
N	570	570	N	570	570

industrial rationalization (*ia*) and supererogation (*ib*) are significantly positive, at least at the 10% level. The spatial weight term of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly positive at least at the 5% level. The spatial weight term of eco-efficiency (*Wbtr*) is significantly positive at the 1% level. To conclude, after testing the endogeneity problem, our baseline results are still robust.

5.6. Heterogeneity analysis

To further investigate the heterogeneous stylized facts of the effects of industrial upgrading on eco-efficiency in Chinese provinces, we divide the data into several sub-samples.

5.6.1. Temporal heterogeneity: before and after the Year 2008

Studies have found that the Global Financial Crisis in 2008 significantly impacted the developing pattern of business and industry worldwide (Berkmen et al., 2012; Reddy et al., 2014; Rao and Reddy, 2015). For China, its trade sectors suffered from major loss of overseas markets and financing constraints (Liang, 2010; Li et al., 2012; Coulibaly et al., 2013), which could force some of the industries to resort from upgrading (Schüller and Schüler-Zhou, 2009; Hausman and Johnston, 2014). Thus, we take the year 2008, during which the Global Financial Crisis exploded, as the boundary to test the temporal heterogeneity. The two sub-samples are the year 1998–2008 and the year 2009–2017. Table 11 presents the empirical results.

Columns 1 and 2 presents the results of the pre-2008 sample. Both industrial rationalization (*ia*) and supererogation (*ib*) are not significant. The spatial weight of industrial rationalization (*Wia*) and supererogation (*Wib*) are also not significant. It implies that before the year 2008 (the Global Financial Crisis), the promoting effects of industrial upgrading on eco-efficiency do not exist, not even to mention the spatial spillover effects.

Columns 3 and 4 are the results after the Global Financial Crisis (post-2008). Industrial rationalization (*ia*) is significantly positive at the 5% level. Industrial supererogation (*ib*) is significantly positive at the 1% level, suggesting that industrial upgrading could promote eco-efficiency

Table 11
Temporal heterogeneity: The impact of the global financial crisis.

Variable	(1)	(2)	(3)	(4)
	Before 2008		After 2008	
Wbtr	0.406***	0.419***	0.725***	0.674***
	(0.102)	(0.101)	(0.063)	(0.069)
ia	0.002		0.037**	
	(0.013)		(0.017)	
Wia	0.031		0.070***	
	(0.033)		(0.023)	
ib		0.055		0.166***
		(0.044)		(0.057)
Wib		0.164		0.223***
		(0.155)		(0.070)
Control Variables	Yes	Yes	Yes	Yes
ll	603.89	603.71	416.37	424.57
R2	0.168	0.168	0.109	0.032
N	330	330	270	270

in the post-Global Financial Crisis ear. Meanwhile, the spatial weight of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly positive at the 1% level, which means that after year 2008 industrial upgrading in one province could significantly promote the eco-efficiency of neighboring provinces. Further, the spatial weights of eco-efficiency (*Wbtr*) are significantly positive at the 1% level in all the columns, indicating that the spatial effects of eco-efficiency are irrelevant to chronological change.

5.6.2. Regulation heterogeneity: various strictness of environmental regulations

We divide the 30 provinces into two groups based on their strictness of environmental regulations. We calculate the mean value of the strictness of environmental regulation (*reg*) of the sample from 1998 to 2017 and observe their median. If the mean value of the strictness of environmental regulation (*reg*) is smaller than the median, then we categorized the province as "low-regulation", otherwise we identify them as "high-regulation". Table 12 presents the empirical results.

Columns 1 and 2 are the results for the low-regulation provinces. Neither industrial rationalization (*ia*) nor industrial supererogation (*ib*) is significant. The spatial weight of industrial rationalization (*Wia*) and supererogation (*Wib*) are also not significant. It means that in low-regulation provinces, the industrial upgrading does not improve eco-efficiency locally and spatially. Columns 3 and 4 are the results of high-regulation provinces. We find industrial rationalization (*ia*) is significantly positive and industrial supererogation (*ib*) are significantly positive at the 1% level, suggesting that industrial upgrading in provinces with stringent environmental regulations could promote eco-efficiency. Moreover, the spatial weight of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly positive at the 1% level, meaning that industrial upgrading in provinces with strict environmental regulations could promote the eco-efficiency of other provinces. At last, the spatial weight of eco-efficiency (*Wbtr*) in are all significantly positive in the four columns, indicating that spatial effects of eco-efficiency exist in both low and high regulation provinces.

5.7. Mechanism analysis

We propose three mechanisms that industrial upgrading could promote eco-efficiency in Chinese provinces, which are economic growth, reduction of pollution, and decrease in energy consumption. Thus, we take the GDP per capita (*ly*), SO2 emission per capita (*lpso2*),[8] and energy consumption per capita (*lpenv*) as dependent variables and industrial upgrading (rationalization and supererogation) as independent variables in the estimation.[9] Tables 13–15 reveal the results of the mechanism analysis.

Table 13 presents the mechanism of economic growth. We find that industrial rationalization (*ia*) and industrial supererogation (*ib*) are significantly positive at 1%, indicating that industrial upgrading could lead to economic growth. The spatial weight of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly positive at the 1% level, suggesting that local industrial upgrading could promote economic growth in neighboring provinces. Further, the spatial weight of GDP per capita (*Wly*) is significantly positive at 1%, indicating that the economic growth of Chinese provinces is spatially correlated.

Table 14 presents the mechanism of pollution reduction. We find that industrial rationalization (*ia*) and industrial supererogation (*ib*) are significantly negative, at least at 5%, suggesting that industrial upgrading could lead to an effective reduction of pollution. The spatial weights of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly negative at the 1% level, which means that local industrial upgrading could effectively reduce the pollution in neighboring provinces. Moreover, the spatial weight term of SO2 emission per capita (*Wlpso2*) is significantly positive at 1%, proving that environmental pollution is spatially correlated.

Table 15 presents the mechanism of the decrease in energy consumption. We find that industrial rationalization (*ia*) and industrial supererogation (*ib*) are significantly negative at least at 10%, suggesting that industrial upgrading could lead to a dramatic decrease in energy consumption. The spatial weights of industrial rationalization (*Wia*) and supererogation (*Wib*) are significantly negative at the 1% level, which means that local industrial upgrading could effectively reduce the energy consumption in neighboring provinces. Moreover, the spatial weight term of energy consumption per capita (*Wlpenv*) is significantly positive at 1%, demonstrating that energy consumption is spatially correlated.

To sum up, we identify that there are three mechanisms. By facilitating economic growth, pollution reduction, and decrease in energy consumption, industrial upgrading promotes eco-efficiency, both locally and spatially, in Chinese provinces.

6. Conclusion and policy implications

Although studies on eco-efficiency are substantial, literature that focuses on industrial upgrading in the process still falls short. The scope of our study included a thorough investigation of the effects of industrial

Table 12
Regulation heterogeneity: Strict or loose.

Variable	(1)	(2)	(3)	(4)
	Low-Regulation		High-Regulation	
Wbtr	0.712***	0.676***	0.397***	0.391***
	(0.045)	(0.048)	(0.082)	(0.084)
ia	0.005		0.051***	
	(0.005)		(0.015)	
Wia	0.015		0.066***	
	(0.018)		(0.024)	
ib		−0.023		0.191***
		(0.030)		(0.061)
Wib		0.113		0.132**
		(0.132)		(0.062)
Control Variables	Yes	Yes	Yes	Yes
ll	619.58	623.55	348.23	350.07
R2	0.764	0.803	0.547	0.534
N	300	300	300	300

Table 13
The mechanism of economic growth.

Variable	(1)	(2)
Wly	0.734***	0.705***
	(0.025)	(0.029)
ia	0.059***	
	(0.011)	
Wia	0.165***	
	(0.029)	(0.075)
ib		0.282***
		(0.030)
Wib		0.226***
		(0.075)
Control Variables	Yes	Yes
ll	585.20	614.52
R2	0.758	0.801
N	600	600

[8] The provincial data of SO2 in China is only available after year 2004.

[9] The three independent variables are in logarithmic form.

Table 14
The mechanism of pollution reduction.

Variable	(1)	(2)
Wlpso2	0.720***	0.700***
	(0.043)	(0.044)
ia	−0.042**	
	(0.021)	
Wia	−0.262***	
	(0.044)	
ib		−0.146**
		(0.069)
Wib		−1.057***
		(0.145)
Control Variables	Yes	Yes
ll	88.97	95.49
R2	0.095	0.063
N	420	420

Table 15
The mechanism of decrease in energy consumption.

Variable	(1)	(2)
Wlpenv	0.646***	0.659***
	(0.034)	(0.035)
ia	−0.032**	
	(0.015)	
Wia	−0.140***	
	(0.030)	
ib		−0.102*
		(0.054)
Wib		−0.419***
		(0.072)
Control Variables	Yes	Yes
ll	475.42	485.20
R2	0.617	0.625
N	600	600

upgrading in promoting eco-efficiency at the provincial level in China. We build a measuring system to estimate the eco-efficiency index by using the GPCA model. A baseline regression model and a spatial effect model are then constructed to examine the local and spatial effects of industrial upgrading on eco-efficiency. We also carry out further examinations to test the robustness, to address the concern of endogeneity, to capture the heterogeneous effects, and to identify the mechanisms. The following conclusions could be drawn: (1) Industrial upgrading, including rationalization and supererogation, could significantly promote eco-efficiency at the provincial level in China. (2) There is a positive spatial spillover effect of industrial upgrading on eco-efficiency at the provincial level in China. Industrial upgrading in a province could promote eco-efficiency in neighboring provinces. (3) The effects of promoting industrial upgrading on eco-efficiency are significant after the year 2008 and in provinces with stringent environmental regulations. (4) The mechanisms by which industrial upgrading promote eco-efficiency are economic growth, pollution reduction, and a decrease in energy consumption.

The structural change of industry is the fundamental momentum for economic growth. In history, developed countries have been through drastic industrial structural change during the First and the Second Industrial Revolution, as well as the information revolution at present. After each major structural revolution, factors flow into sectors and industries with higher efficiency and returns, reducing resource consumption and pollutant emission. Moreover, the higher income level in society also allows for the improvement of environmental awareness. Take Japan and the Four Asian Tigers[10] as an instance. These newly industrialized economies experienced significant industrial upgrading from agriculture to labor-intensive manufacturing and capital-intensive industries (e.g., services and high-end manufacturing industries). By shifting upward in industrial structure, they are now maintaining a high level of eco-efficiency. This process is now happening again in emerging markets. China has already finished the labor-intensive manufacturing section and is now striving for the next round of structural upgrading to capital-intensive industries. Other emerging markets like India, Vietnam, and Indonesia are still working on shifting from agricultural sectors to labor-intensive industries. The heterogeneity of industrial structure between various emerging countries is also reflected in the environmental sustainability in each country, which could partly explain why most of the cities in the top polluted list are from India but not from China.

Our study also provides the following policy implications. First, policies that are conducive to industrial upgrading should be carried out decisively. Keeping the industrial structure in the traditional pattern without changing it could slow progress in improving eco-efficiency. Second, there are two dimensions for the government to consider when promoting industrial upgrading. By rationalization, the government is advised to adjust the ratio between various industries, preventing over-dependence on one or two industries. By supererogation, policies and fiscal subsidies should be in place to encourage technological progress and innovation, thus accelerating the growth of smart manufacturing and modern services industries. Third, the spatial effects of industrial upgrading on eco-efficiency ask for more vital collaboration among regional governments. The central government is advised to act as a coordinator between regional governments to help them design suitable policies in facilitating industrial upgrading, avoiding the risks brought by the contradiction among regional policies. Last, the government should attract green FDI by providing more favorable conditions to foreign companies that are eco-efficient and could provide positive spillovers. Besides, supporting the development of green power industries like hydrogen fuel and solar power is another sensible way to promote eco-efficiency via industrial upgrading. The countries aim to improve their economies and industries, without getting trapped in the "economy or environment" dilemma, such as India, are positively expected to seek policy experiences from China.[11]

There is still room for future studies. First, future research could be carried out in other emerging economies, to examine the robustness of this paper. Second, there can be further studies on the factors that are influencing the effects of industrial rationalization and supererogation. Third, there is even greater room for employing advanced methods and carrying out more tests to identify the mechanisms or channels of how industrial upgrading is affecting eco-efficiency. Besides, the eco-efficiency index should also be improved and revised in different countries.

CRediT authorship contribution statement

Yonghui Han: Conceptualization, Methodology, Supervision,

[10] The Four Asian Tigers refer to Hong Kong SAR, Singapore, South Korea, and Taiwan. From the 1960s to the 1990s, the four economies successfully received industrial transfers from Japan and other developed countries. They underwent rapid industrialization and maintained drastically high growth rates of more than 7% annually.

[11] Chinese experiences, for example, in the case of Sovereign Wealth Funds and their contribution to the industries and economic development for China and for countries around the world, are inspiration to several other emerging and developing countries (Reddy, 2019).

Software. **Fan Zhang:** Writing – original draft, Writing – review & editing, Visualization. **Liangxiong Huang:** Data curation, Software, Writing – original draft. **Keming Peng:** Visualization, Investigation. **Xianbin Wang:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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