Master's Thesis

Industrial eco-efficiency and its determinants in China: Two-stage approach

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July 2020

Abstract:

This study evaluates the provincial industrial eco-efficiency and figure out the determinants of eco-efficiency scores by Two-stage approach. In the first stage, based on panel data of 30 provinces in China from 2005 to 2015, this research carried out a data envelopment analysis (DEA) of provincial eco-efficiency in Chinese industry. The results confirm that the overall trend of industrial eco-efficiency was upward, indicating that China's industrial development is no longer focused on the pursuit of economic benefit but intent on reducing energy intensity and the emission of major pollutants. However, many technological, policy, and industrial eco-efficiency deficiencies remain in numerous regions. In the second stage, we used random-effects Tobit models regression models to evaluate the external factors that can affect the industrial eco-efficiency scores that were determined via DEA. The regression results showed that the internal expenditure of research and development funding in industrial enterprises, per capita gross domestic product, and investments in wastewater exerted positive and significant effects on provincial industrial eco-efficiency, while investment in solid waste was not statistically significant. By contrast, the proportion of state-owned enterprises and investments in waste gas had negative and significant impacts.

Keywords: data envelopment analysis (DEA), provincial-level analysis, industrial eco-efficiency, random-effects Tobit model

Contents

List of Tables and Figures

1. Introduction

1.1 Background

China has undergone momentous changes and gained remarkable economic achievements since its economic reform and opening in 1978—a rapid industrial growth that tremendously contributed to China's economic development. The industrial added value has rapidly increased six-fold from 4.03 trillion yuan in 2000 to 23.65 trillion yuan in 2015 (National Bureau of Statistics, 2005-2015). Undoubtedly, the rapid industrial growth greatly contributed to China's economic development. At the same time, however, the consequent resource depletion and environmental degradation have seriously restricted the sustainable advancement of China's economy. For instance, China's industrial energy consumption in 2015 was 2.8 times as much as that of 2000 (National Bureau of Statistics, 2005-2015). Therefore, an important requirement for governments is to better coordinate the relationship among economic development, environmental protection, and energy conservation.

To achieve sustainable development, the Chinese government takes environmental problems seriously and has enacted a number of environmental laws and regulations with the intention of improving environmental quality. Eco-efficiency is generally measured as the ratio between the value of what has been produced (e.g. GDP) and the environmental impacts for the production and has been seen as one of the main tools to transform unsustainable development to sustainable development. The vast disparity in industrial development among different regions in China requires differentiated policy measures on energy conservation and emission reduction. As a reference for environmental policy and regulation in the national and provincial levels, it is important to correctly evaluate and understand industrial eco-efficiency and its influencing factors in different provinces. Hence, this empirical study evaluates the industrial eco-efficiency scores in China at the provincial level and also analyzes the influencing factors of the eco-efficiency scores.

1.2 Literature review

In 1990, Schaltegger et al. (1990) initially described the concept of eco-efficiency. The widely accepted definition of eco-efficiency is that it is achieved by the delivery of competitively priced goods and services that satisfy human needs and increase the quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity (Schmidheiny and Stigson, 2000). This means to create more value with less environmental impact. As eco-efficiency reflects the comprehensive degree of coordination among economy, resources, and environment, producing more desirable production and reducing resource consumption as well as the undesirable outputs should be considered simultaneously (Huang et al., 2018). Hence, the eco-efficiency can also be seen as an effective tool to apparently show the environmental performance. There is a growing body of literature that deeply elucidates the importance of eco-efficiency. For instance, Huang et al. (2018) argued that eco-efficiency is of great importance in facilitating a regional sustainable development. More crucially, measuring eco-efficiency offers policymakers with critical information for designing policies, which shall integrate local economic activities and the environment for regional sustainable development (Toma et al., 2016).

Data envelopment analysis (DEA) is a method that can accommodate various desirable and undesirable effects of production in a single efficiency index. Hence, DEA can be a useful tool to identify and characterize comprehensive efficiency by simultaneously considering multiple inputs and outputs. There have been wide applications of this approach in various fields. With regards to energy and industrial efficiency, for instance, Hu and Wang (2006) analyzed the energy efficiency of 29 provinces in China for the period 1995–2002 with a traditional DEA. They showed that regional energy efficiency in China has generally improved during the research period except for the western area. Tone and Tsutsui (2011) applied a modified nonparametric DEA to analyze the eco-efficiency of 30 electric utilities in United States between 1996 and 2000 and found that the utilities improved their overall management and environmental efficiency between 1996 and 2000. Chen and Golley (2014) combined standard DEA with the directional distance function to estimate the 'green' total factor productivity growth of 38 Chinese industrial sectors from 1980 to 2010. They revealed that the Chinese industry has not yet been on the path towards the sustainable, low-carbon growth. Dai et al. (2016) implemented the super efficiency DEA while Huang et al. (2018) constructed a measurement system for composite eco-efficiency indicators and proposed a new system based on DEA approach, which simultaneously considers meta-frontier, undesirable outputs, super efficiency, and slacks. They all showed that the provinces in east China have relatively high industrial eco-efficiency. Likewise, Xing et al. (2018a) combined the traditional DEA and economic input-output life cycle assessment to evaluate the environmental impacts and eco-efficiency of China's 26 industrial sectors. They indicated that over 70% of China's economic sectors were inefficient and required significant improvements. Xie et al. (2019a) combined super-efficiency DEA and a Gini criterion approach to assess the environmental performance of industries. The main empirical result suggested that the ranking of the environmental efficiency of various industries overall varies greatly by time. Apparently, DEA is widely used for comparing a set of homogenous DMUs by evaluating their relative efficiency (Ebrahimnejad et al., 2014). A common feature of the above studies is that they explored the efficiency scores, but did not analyze the determinants of the efficiency scores.

Some researchers have further explored the determinants of efficiency score calculated by DEA. Lv et al. (2012) used a sample of 30 provinces for the period 1998–2009 to measure Chinese regional energy efficiency change and its determinants by the basic DEA and random-effect Tobit regression model. From the Tobit regression, they found that the share of electricity consumption in total energy consumption and the share of state-owned industrial output to area gross industrial output value have positive impacts on energy efficiency, while the percentage of the added value of the secondary industry in GDP has a negative influence on energy efficiency. Likewise, Pan et al. (2013) used the extended DEA model and random-effect Tobit regression model to explore China’s provincial industrial energy efficiency and determinants. Their regression analysis showed that higher energy efficiency was resulted from higher marketization level, higher GDP per capita, higher R&D expenditure per capita, and lower coal consumption percentage. Although Lv et al. (2012) and Pan et al. (2013) applied the two-stage approach, they focused on energy efficiency without comprehensively considering the undesirable outputs (i.e., environmental issues), such as CO_2 and waste emissions, which is inadequate when evaluating the degree of sustainable industrial development. There are other extant studies using regression analysis as second stage to explore the determinants of efficiency score calculated by DEA. By the application of regression method, the researchers found the determinants of the efficiency of various objectives, such as firms in the pharmaceutical industry (Tripathy et al., 2009), industrial sectors (Ahmad et al., 2017, Chen and Golley, 2014), bank in China (Huang et al., 2014), tomato production (Raheli et al., 2017).

Although the combined application of DEA and regression analysis is widely used in various fields, regarding provincial industrial eco-efficiency, many previous studies only evaluated the efficiency score by DEA but did not further explore the determinants of industrial eco-efficiency. For purposes of policy implications in efficiency analysis, it is very important to identify determinants that influence efficiency (Raheli et al., 2017). Therefore, this study uses a two-stage estimation approach to evaluate the provincial industrial eco-efficiency and their determinants, which is conducive to give guidance to improve industrial eco-efficiency.

1.3 Purpose

The purpose of this paper is to evaluate the provincial industrial eco-efficiency and figure out the determinants of eco-efficiency scores. The contributions of this study are as follows. First, the DEA model is used to perform the provincial eco-efficiency analysis based on the latest data available. The input, desirable output and undesirable output variables are comprehensively considered. The characteristics of provincial industrial eco-efficiency in China was found via DEA. Furthermore, regression analyses are conducted to evaluate the determinants that influence the industrial eco-efficiency scores calculated by DEA. The regression results can advance the identification of determinants that are effective to improve the industrial eco-efficiency. In addition, existing studies only calculated the eco-efficiency scores, but they did not give a detailed explanation of the results based on the region-specific characteristics. Hence, in this paper, five provinces of the northern region are selected to provide provincial insights on the eco-efficiency scores. The results allow policymakers to better integrate economic activities and the environmental consideration.

The remainder of this paper proceeds as follows. Section 2 gives the methods, introducing the DEA model for undesirable output, regression model, data sources, variables description. The results and discussion of provincial industrial eco-efficiency score evaluated by DEA and determinants of eco-efficiency were presented in section 3. Section 4 makes a conclusion and policy implications.

2. Data and methods

In this section, the data and methods used in this study are introduced. In our empirical study, DEA is used to calculate the regional industrial eco-efficiency and then perform the regression analysis to further figure out the possible determinants of the efficiency scores. In both analyses, panel data were applied.

2.1 Variables and data

In this section, the variables selected as input and output used for the DEA model to evaluate the industrial eco-efficiency and the variables selected as determinants are introduced. The samples are 30 provincial-level administrative units (provinces) in mainland China from 2005 to 2015 except for Tibet Autonomous Region because of data availability.

With regard to the selection of variables used for the DEA model, capital and labor are usually selected as input variables (Feng and Wang, 2017, Wu et al., 2019, Zhao et al., 2020, Matsumoto et al., 2020) because capital and labor are important and definitely necessary to produce goods and services. At the same time, it is imperative to improve the industrial energy and water resource utilization efficiency because China is faced with severe energy and water shortage (Zou and Cong, 2020, Hu and Wang, 2006). Hence, capital, labor, total energy consumption and industrial water supply and use are selected as input variables in this study. As Korhonen and Luptacik (2004) mentioned, additional indicators are needed to measure the environmental performance of the firm and the national economy. Thus, environmental burdens such as waste gas, wastewater, solid waste, and CO_2 emission should be used as indicators to evaluate industrial eco-efficiency (Feng and Wang, 2017, Lv et al., 2012, Chen and Golley, 2014).

In this study, to comprehensively evaluate the provincial industrial eco-efficiency in China considering both representativeness and availability of data, the selected input variables are total energy consumption, the total assets of industrial enterprises, labor, and industrial water supply and use. The output variables were classified into desirable output variables, the industry value added, and undesirable output variables, waste gas, wastewater, solid waste, and CO_2 emission. All the variables are in annual basis.

All the data for pollutant emissions, except for CO_2, are directly retrieved from the (National Bureau of Statistics, 2005-2015). However, there are no officially published data for industrial CO_2 emissions. Hence, the CO_2 emissions were calculated using energy consumption data extracted from (National Bureau of Statistics, 2005-2015) (eq. (1)).

$$CARB_i = \sum_j FUEL_{ij} = FUEL_{ij} \times SC_j \times SEC_j \times \frac{44}{12} \quad (1)$$

where *CARB* represents CO_2 emissions (in tons of CO_2), *FUEL* represents the total industrial consumption of different energy types (in tons), *SC* represents the conversion coefficient of standard coal for different energy types (ton of standard coal per ton of energy), *SEC* denotes the carbon emission coefficient (in tons of carbon per ton of standard coal), *i* represent each province, while *j* means different types of fossil fuels.

Table 1 **The coefficiency of standard coal conversion and carbon emission by energy type**

Energy type	**Standard coal conversion coefficient (ton of standard coal/ton of energy)**	**Carbon emission coefficient (ton of carbon/ton of standard coal)**
Coal	0.7143	0.7559
Coke	0.9714	0.8550
Crude oil	1.4286	0.5857
Fuel oil	1.4286	0.6185
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel	1.4571	0.5921
Natural gas	1.33×10^{-3}	0.4483
LPG	1.7143	0.5042

Sources: National Bureau of Statistics of China (2005-2015) and Intergovernmental Panel on Climate Change (2006)

The other data used in the DEA model are obtained from several official statistical yearbooks shown in Table 2. The following Table 3 shows the descriptive statistics of the input and output variables.

Table 2 Input and output variables used in DEA model and data sources

Category	Variable	Unit	Data Sources
Input	Total energy Consumption	10000 tons of Standard Coal Equivalent	National Bureau of Statistics of China (2005-2015)
	Total assets of industrial enterprises	10000 yuan	National Bureau of Statistics of China (2005-2015)
	Annual average number of employments	person	National Bureau of Statistics of China (2005-2015)
	Industrial water supply and use	100 million cubic meters	China statistical yearbook on environment (2006-2016)
Undesirable output	Industrial waste gas emission	100 million standard cubic meters	China statistical yearbook on environment (2006-2016)
	Industrial wastewater	10000 tons	China statistical yearbook on environment (2006-2016)
	Common industrial solid wastes disposed and keep in storage	10000 tons	China statistical yearbook on environment (2006-2016)
Desirable output	Industrial added value	10000 million	National Bureau of Statistics of China (2005-2015)

Table 3 Descriptive statistics of the input and output variables used in DEA model

Variable	Mean	SD	Min	Max
Total Energy Consumption	8898.47	6126.27	465.09	30070
Total assets of industrial enterprises	191598596.97	188537157.40	7032000	1070617273
Annual average number of employed persons	293.95	319.56	10.3	1568
Industrial water supply and use	46.12	45.03	2.4	239
Industrial waste gas emissions	17263.75	13948.96	859.7	79121.3
Industrial wastewater	82173.26	74284.33	5782.2	341607.41
Common industrial solid wastes disposed and keep in storage	3150.01	4228.81	10.18	28237.15
CO_2 emissions	228.6	163.30	12	729.84
Industrial added value	6387.05	6006.95	176.92	30259.49

As for the data used for the regression analyses, six independent variables are selected for the determinants, which potentially have significant impacts on industrial eco-efficiency. These variables are per capita GDP, internal expenditure of research and development funds of industrial enterprises, the proportion of the state-owned enterprises, investment in wastewater, investment in waste gas, investment in solid waste. The data sources and descriptive statistics for all determinants used in regression models are shown in Tables 4 and 5.

Table 4 Possible determinants of industrial eco-efficiency and data sources

Determinants	Unit	Data sources
Internal expenditure of R&D funds of industrial enterprises (*R&D*)	Ten thousand yuan	China statistical yearbook on environment (2006-2016)
The proportion of state-owned enterprises (*PSO*)	-	National Bureau of Statistics of China (2005-2015)
Per capita GDP (*GDP*)	yuan/person	National Bureau of Statistics of China (2005-2015)
Investment in wastewater (*IWW*)	Ten thousand yuan	National Bureau of Statistics of China (2005-2015)
Investment in waste gas (*IWG*)	Ten thousand yuan	National Bureau of Statistics of China (2005-2015)
Investment in solid waste (*IWS*)	Ten thousand yuan	National Bureau of Statistics of China (2005-2015)

Table 5 Descriptive statistics of possible determinants of industrial eco-efficiency

External factors	Mean	SD	Min	Max
Internal expenditure of R&D funds of industrial enterprises (R&D)	1971832	3029478.00	38	16500000
The proportion of state-owned enterprises (PSO)	0.12	0.08	0.01	0.40
Per capita GDP (GDP)	34941.98	21574.07	5052	107960
Investment in wastewater (IWW)	48379.41	47955.72	90	295540
Investment in waste gas (IWG)	104547.6	127534.10	140	1281351
Investment in solid waste (IWS)	7407.674	10755.89	1	77997

2.2 Determinants of industrial eco-efficiency

The reasons for selecting *R&D, PSO, GDP, IWW, IWG, IWS* as determinants of industrial eco-efficiency are described in this section.

The increasing per capita GDP may have a positive influence on industrial eco-efficiency. Per capita GDP is treated as a proxy of economic development. To explore the connection of economic development and environmental degradation, the environmental Kuznets curve (EKC) was gradually proposed and verified in many countries and regions (Badeeb et al., 2020). EKC indicates that when the economic development reaches a certain level, with the further increase of per capita income, environmental pollution will gradually decrease, and the environmental quality will gradually be improved (Shi et al., 2020). Based on the evidences found by Xie et al. (2019b) , most provinces in China have already crossed the EKC turning point in 2005 that with the increase of per capita GDP, the residents' requirements for the quality of environment become higher, the government has to increase the expenditure on environmental protection and then promote the transformation of enterprises to the mode of cleaner production. Therefore, it seems that higher per capita GDP will contribute to higher industrial eco-efficiency score.

The increasing of internal expenditure of R&D funds of industrial enterprises may have a positive influence on industrial eco-efficiency. Prior studies have noted that R&D has a significant positive impact on the environment (Matsuoka, 2009, Zhao et al., 2019, Xing et al., 2018b). Industrial R&D is the main driver of innovation and internal expenditure of R&D fund can be used as the key indicator to monitor resources devoted to science and technology (Savrul and Incekara, 2015). In this study, the R&D investment is considered to have a positive impact on industrial eco-efficiency because environmental performance is deeply related to technological progress. Moreover, a one-year lag (i.e., data in 2004 were used for year 2005) was applied in the regression model to allow enough time for the expenditure of R&D funds to take effect.

The investment in industrial pollution control may have a positive influence on industrial eco-efficiency because its objective is to assist in the implementation of the government's policy on pollution abatement. In this study, the investment in industrial pollution control contains three aspects: that in wastewater, waste gas, and solid waste. the investment in industrial pollution control is considered to contribute to improving industrial eco-efficiency by reducing pollutants. A one-year lag was also applied in the regression model.

The increasing of the proportion of state-owned enterprises may have a negative influence on industrial eco-efficiency. The common understanding from previous is that state-owned enterprises are less efficient than other types of ownership (Liu et al., 2020, Lin et al., 2020). The first reason is that the state-owned enterprises are owned by the people conceptually, and such an ambiguous definition of property rights lead to excessive consumption of resources in the state-owned enterprises by the state, managers, and workers (Lin et al., 2020). The second one is that the controlling shareholder of state-owned enterprises is the government, whose primary aim is not pursuing economic benefits but maintaining social stability, such as reducing unemployment and wage gaps (Lin et al., 1998). Accordingly, the higher proportion of state-owned enterprises may induce lower industrial eco-efficiency score.

2.3 Method

2.3.1 DEA

DEA model was initially proposed by Charnes et al. (1978). The model, called the CCR model, is a popular linear non-parametric mathematical programming approach used to determine the relative efficiency of homogenous DMUs. DEA can develop from a single-input/single-output technical efficiency measure to the multiple-input/multiple-output case and the weights for each DMU's inputs and outputs are not affected by subjective factors. The most efficient DMUs constitute the efficient frontier and the efficiency score of remaining DMUs is the relative efficiency.

With more attention has been paid to the ecological conservation, development of technologies with smaller undesirable outputs (i.e., environmental burdens) is an important subject of concern in every area of production. The conventional DEA supposes that producing more outputs with less input resources is a criterion of efficiency. In the presence of undesirable outputs, however, technologies with more desirable (good) outputs and less undesirable (bad) outputs relative to less input of resources should be recognized as efficient.

Four most commonly used methods in treating undesirable outputs in DEA include: (1) ignoring them from the production function; (2) treating them as regular inputs; (3) treating them as normal outputs; and (4) performing necessary transformations to take them into account (Halkos and Petrou, 2019). In this study, the third one is employed, i.e., the undesirable outputs are treated as normal outputs in a slack based model (SBM).

Firstly, the definition of the symbols that will be used is introduced as follows. n is the number of DMUs, m is the number of inputs, s_1 means the number of desirable outputs, s_2 means the number of undesirable outputs, λ is the vector for projecting the DMUs, Suppose that there are *n* DMUs each has three types of factor (inputs, desirable outputs, and undesirable outputs) as represented by three vectors $\chi, \gamma^g, and\ \gamma^b$, respectively. The matrices X, Y^g, and Y^b are defined as follows. $X = (\chi_1, \dots, \chi_n) \in R^{m \times n}$, $Y^g = (\gamma_1^g, \dots, \gamma_n^g) \in R^{s_1 \times n}$, and $Y^b = (\gamma_1^b, \dots, \gamma_n^b) \in R^{s_2 \times n}$. We assume $X > 0, Y^g > 0,$ and $Y^b > 0$.

The production possibility set (P) is defined as eq. (2):

$$P = \{(\chi, \gamma^g, \gamma^b) | \chi \geq X\lambda, \gamma^g \leq Y^g\lambda, \gamma^b \geq Y^b\lambda, \lambda \geq 0\}, \tag{2}$$

where $\lambda \in R^n$ is the intensity vector. Notice that the above equation corresponds to the constant returns to scale technology.

A DMU$_o$ $(\chi_o, \gamma_o^g, \gamma_o^b)$ is efficient in the presence of undesirable outputs if there is no vector $(\chi, \gamma^g, \gamma^b) \in P$ such that $\chi_0 \geq \chi, \gamma_o^g \leq \gamma^g, \gamma_o^b \geq \gamma^b$ with at least one strict inequality.

In accordance with this definition, SBM is modified as follows to develop the SBM with undesirable outputs (eq. (3)).

$$\text{Min } P^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{\chi_{io}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{\gamma_{ro}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{\gamma_{ro}^b}\right)}$$

Subject to

$$\begin{gathered} \chi_o = X\lambda + s^- \\ \gamma_o^g = Y^g\lambda - s^g \\ \gamma_o^b = Y^b\lambda + s^b \\ s^- \geq 0. s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{gathered} \tag{3}$$

where *i* means the index for inputs (1, 2..., m), s^- is the value of slack for the inputs, s^g is the value of slack for the desirable outputs, s^b is the values of slack for the undesirable outputs. The vectors $s^- \in R^m$ and $s^b \in R^{s_2}$ correspond to excesses in inputs and undesirable outputs, respectively, while $s^g \in R^{s_1}$ expresses shortages in good outputs. P^* reaches 1 only if slacks $s^-, s^g,$ and s^b are zero in all inputs, desirable outputs, and undesirable outputs.

It should be noted that in DEA, when the number of DMUs is small, the number of units of the dominant or efficient set is relatively large and the average efficiency is generally high (Homanmad, 1998). In general, a high proportion of the DMUs will be treated as efficient when the number of DMUs (n) is less than the sum of input (m) and output (s) variables (i.e., $n < m + s$), and lead to low discrimination between homogeneous units (Matsuoka, 2009). Hence, it is better that $n > m + s$. A rough rule of thumb in the DEA model is that the number of DMUs should be equal to or greater than max{$m \times s$, $3 \times (m+s)$} (Doyle and Green, 1994). In this study, this condition is satisfied.

2.3.2 Random-effects Tobit model

In order to examine the effect of factors that affect industrial eco-efficiency of provinces, random-effects Tobit models are used as the second-stage analysis. The two-stage approach that combines DEA with a regression method is appealing both in terms of its simplicity and the way the efficiency is described and interpreted (McDonald, 2009). Since the efficiency scores are bounded, there is no consensus on the method to be applied in the second stage and a variety of regression techniques have been used, including the classic ordinary least squares (OLS) and Tobit regression (Yahia and Essid, 2018). Because the value of efficiency scores obtained from DEA is limited to the interval of 0 to 1, the DEA scores are censoring variables; thus OLS will provide biased estimates (Agasisti and Cordero-Ferrera, 2013). In this case, the limited dependent variable model (Tobit model) is used to avoid this problem. Hoff (2007) pointed that in most cases the Tobit model is sufficient for modelling DEA scores against exogenous variables. Hence, in this study, random-effects Tobit model regressions are performed to avoid bias from the choices of regression models.

As mention in section 2.2, internal expenditure of R&D funds of industrial enterprises (*R&D*), the proportion of state-owned enterprises *(PSO*), per capita GDP (*GDP*) and its squared term, investment in wastewater (*IWW*), investment in waste gas (*IWG*), investment in solid waste (*IWS*) are included in the basic model as the control variables, Tobit analysis can be explained with the following mathematical expressions:

$$y_{it} = \beta_1 R\&D_{it} + \beta_2 PSO_{it} + \beta_3 GDP_{it} + \beta_3 GDP_{it}^2 + \beta_4 IWW_{it} + \beta_5 IWG_{it} + \beta_6 IWS_{it} + \alpha + u_{it} \tag{4}$$

$$\begin{cases} y_{it} = 0 & if y_{it}^* \leq 0 \\ y_{it} = 1 & if y_{it}^* \geq 1 \\ y_i = y_{it}^* & if 0 < y_{it}^* < 1 \end{cases}$$

where y_{it} is the eco-efficiency score evaluated by DEA, y_{it}^* is the unobserved latent variable, *i* is the index of each province, *t* denotes year, β is the vector of unknown parameters which determines the relationship between the independent variables and the latent variable, α is the intercept, and u_{it} is the error term.

Generally, it is argued that the observed efficiency scores y_{it}^* is censoring below zero and above one. The regression analyses are conducted by Stata.

3. Results and discussion

3.1 Data envelopment analysis

In this article, 30 provinces in China are treated as DMUs. Table 6 summarizes the industrial eco-efficiency scores of the 30 provinces from 2005 to 2015. Two points of interest are as follows. First, the industrial eco-efficiency scores of some provinces tended to first increase drastically before eventually declining. For example, the scores of Hebei, Zhejiang, Fujian, Jiangxi, Henan, Hunan, and Guangxi dramatically rose to 1 in 2010 but suddenly dropped in the following year. In 2010, these provinces announced regulations for preventing and controlling industrial pollution and generally the enforcement was stricter when the regulations were first promulgated compared with the succeeding years (Yuan and Zhang, 2020).

Second, the results depict that the overall trend of industrial eco-efficiency is upward. However Chinese provinces still face considerable regional disparity in industrial eco-efficiency. The results show that apart from some provinces, the industrial eco-efficiency of China is generally low. In 2015, Beijing, Tianjin, Inner Mongolia, Hunan, and Guangdong, showing the efficiency score of 1, were more efficient than other provinces. Provinces with the worst industrial eco-efficiency in 2015 were Ningxia (0.251), Shanxi (0.253), Gansu (0.273), Xinjiang (0.309), and Qinghai (0.356). It is worth noting that four of these provinces, except for Shanxi, are located in the northwest, which is characterized as the undeveloped economy and fragile ecology. The result apparently reveals that the development of industry in northwest China is extremely backward comprehensively considering economic, energy, and environmental aspects. It is suggested that the Chinese government should focus on dealing with the unbalanced development of its provincial industrial eco-efficiency (Chen and Jia, 2017).

Table 6 Industrial eco-efficiency score in China from 2005 to 2015

Region	Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
	Beijing	0.287	0.300	0.340	0.371	0.415	0.486	0.606	0.768	0.825	1.000	1.000	0.582
	Tianjin	0.457	0.501	0.568	0.774	0.625	1.000	1.000	1.000	1.000	1.000	1.000	0.811
North	Hebei	0.441	0.471	0.508	0.591	0.616	1.000	0.615	0.621	0.630	0.503	0.477	0.588
	Shanxi	0.256	0.259	0.291	0.330	0.311	0.359	0.402	0.368	0.339	0.315	0.254	0.317
	Inner Mongolia	0.318	0.362	0.425	0.639	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.795
	Liaoning	0.284	0.292	0.310	0.362	0.441	0.573	0.526	0.565	0.568	0.582	0.537	0.458
Northeast	Jilin	0.289	0.327	0.387	0.440	0.592	0.529	0.722	0.795	1.000	1.000	0.752	0.621
	Heilongjiang	0.494	0.539	0.536	0.567	0.446	0.553	1.000	0.660	0.587	0.493	0.419	0.572
	Shanghai	0.369	0.390	0.410	0.422	0.407	0.464	0.509	0.525	0.493	0.623	0.584	0.472
	Jiangsu	0.402	0.413	0.425	0.443	1.000	0.766	0.460	0.477	0.481	0.487	0.499	0.532
	Zhejiang	0.381	0.398	0.392	0.427	0.830	1.000	0.516	0.583	0.630	0.736	0.775	0.606
East	Anhui	0.303	0.323	0.344	0.360	0.457	0.552	0.516	0.544	0.557	0.539	0.483	0.453
	Fujian	0.390	0.395	0.395	0.436	0.752	1.000	0.565	0.635	0.633	0.649	0.674	0.593
	Jiangxi	0.384	0.461	0.473	0.526	0.715	1.000	0.782	0.778	0.759	0.707	0.590	0.652
	Shandong	0.536	0.594	0.561	0.665	1.000	0.913	0.615	0.621	0.584	0.566	0.551	0.655
	Henan	0.467	0.527	0.585	0.719	0.801	1.000	0.743	0.704	0.545	0.496	0.470	0.642
Central	Hubei	0.276	0.448	0.318	0.353	1.000	0.495	0.512	0.575	0.544	0.553	0.575	0.514
	Hunan	0.366	0.444	0.445	0.538	0.756	1.000	0.733	1.000	1.000	1.000	1.000	0.753
	Guangdong	0.461	0.488	0.524	0.564	0.567	0.714	0.845	1.000	0.777	0.864	1.000	0.709
South	Guangxi	0.330	0.368	0.416	0.470	0.570	1.000	0.656	0.727	0.647	0.706	0.759	0.604
	Hainan	0.278	0.322	0.316	0.351	0.389	0.411	0.437	0.461	0.366	0.417	0.369	0.374
	Chongqing	0.419	0.414	0.473	0.559	0.501	0.616	1.000	1.000	0.579	0.566	0.599	0.611
Southwest	Sichuan	0.280	0.314	0.325	0.378	0.485	0.551	0.489	0.536	0.530	0.518	0.477	0.444
	Guizhou	0.226	0.236	0.253	0.275	0.288	0.364	0.259	0.332	0.370	0.384	0.392	0.307
	Yunnan	0.296	0.309	0.310	0.358	0.408	0.466	0.375	0.401	0.399	0.403	0.410	0.376
	Shaanxi	0.344	0.401	0.419	0.492	0.488	0.591	0.681	0.936	1.000	0.673	0.573	0.600
	Gansu	0.218	0.257	0.283	0.288	0.300	0.356	0.361	0.357	0.353	0.345	0.273	0.308
Northwest	Qinghai	0.196	0.215	0.251	0.295	0.299	0.345	0.459	0.488	0.390	0.402	0.356	0.336
	Ningxia	0.173	0.200	0.232	0.272	0.257	0.271	0.280	0.272	0.264	0.252	0.251	0.248
	Xinjiang	0.352	0.420	0.371	0.376	0.370	0.494	0.463	0.447	0.364	0.358	0.309	0.393

Other findings, for example, are that five provinces (Beijing, Tianjin, Inner Mongolia, Hunan, Guangdong) have great progress that their industrial eco-efficiency improved more than 0.5 from 2005 to 2015, while other provinces have no significant progress (e.g., Hebei, Shandong, and Henan). There still exist three provinces (Shanxi, Shandong, and Xinjiang) experiencing the decline in industrial eco-efficiency. This indicates that although some Chinese local governments changed from pursuing economic growth but ignoring environmental protection to emphasizing the balance of both environmental protection and economic growth, many provinces still have not been lifted out of the situation of high consumption of water and energy, and heavy pollution.

The reason that many provinces have no significant progress in industrial eco-efficiency scores, or even be worse, was presumably the fundamental conflict of interest between the central government and the local government. In China, national laws and regulations on environmental protection are formulated by the central government but are fleshed out according to the actual situation of each region and implemented at the local level (Zheng et al., 2015). This is because the central government represents the general interests of the whole country and the public, while the local government may take the maximization of the local economic interests as the main goal. As a result, the central government's policies cannot be fully implemented by local government. There are many problems in the implementation of policies of the central governments, and there is a big gap between the effect and expectations of policies, or even completely deviate from the original intention of the central government. In order to improve the industrial eco-efficiency, the implementation of policies cannot be separated from actual participation by the local government. To deal with these problems, the central government should build a system that gives clear guidance on the mandatory responsibility of local governments in the development and implementation of environmental protection actions. Furthermore, the local governments should set a more tangible target to respond to the central government’s laws and regulations on environmental protection in accordance with their actual conditions, strengthen enforcement of regulations in addition to adoptions of cleaner production, energy-saving, and comprehensive resource utilization policies, and through revisions of local standards for emissions reduction (Zheng et al., 2015).

The north region is selected to further discuss on the change trend of industrial eco-efficiency below because it contains the provinces with the best as well as the nearly worst eco-efficiency performance. Figure 1 depicts the trend of industrial eco-efficiency of the provinces in the North China during 2005–2015.

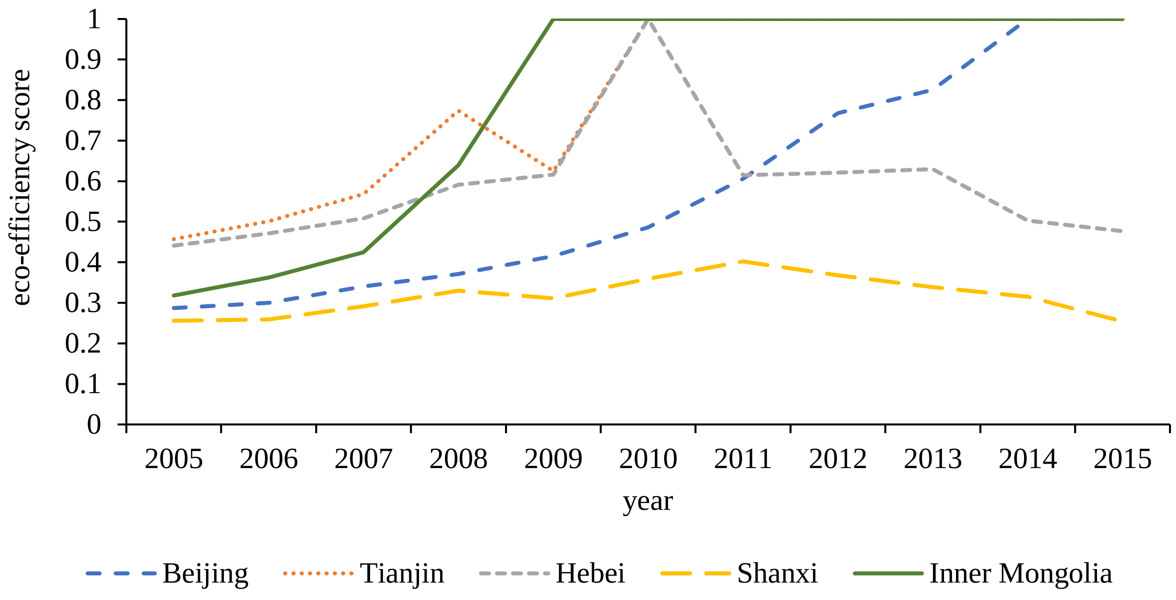

Figure 1. Industrial eco-efficiency in North China

An important finding is that Beijing has experienced the great progress during the study period. Beijing is the capital city of China, which had the distinction of being a polluted city. The eco-efficiency score was only 0.287 in 2005, which is comparatively low in China but increased rapidly and achieved 1 in 2014. This finding is consistent with the finding that the health of green development generally improved in Beijing from 2000 to 2014 (Wu et al., 2018). This achievement is likely to relate to the fact that Beijing continued working to improve policies and legislation on environmental protection, strictly supervise their implementation, rectify polluting businesses, and promote cleaner production. Beginning in 2006, many large-scale industrial enterprises such as Beijing Coking and Chemical Plant, Beijing Capital Steel Group Shougang Shijingshan Plant, and Dongfang Chemical Plant were closed or moved to other provinces (He et al., 2019). As of the end of 2013, 288 polluting enterprises have been closed through adjustment in the city, exceeding the annual goal of 200 polluting enterprises, involving 11 sectors such as building materials, chemical industry, furniture, casting and forging (Beijing Municipal Ecology and Environment Bureau, 2013). In addition, the Beijing Clean Air Action Plan was issued in 2011 (The People's Government of Beijing Municipality, 2011) and contributed to the decrease in industrial gas emission from 489.6 billion m^3 in 2011 to 367.6 billion m^3 in 2015. Furthermore, the Municipal People's Congress voted to adopt the regulations of Beijing on the prevention and control of air pollution, which came into effect on March 1, 2014. Since then, the implementation of "the catalog of prohibitions and restrictions on new industries" has more effectively controlled the industrial expansion that does not conform to the strategic positioning of the capital's functions and guided the industry to continue to develop in the direction of low-carbon and green economy (Beijing Municipal Ecology and Environment Bureau, 2013). In addition, in the past 10 years, Beijing have greatly increased the standard of sewage charges by 10 times. At the same time, sewage charging policy is implemented step-by-step to encourage enterprises to adopt advanced technology progressively and actively control pollution and reduce emissions (Don et al., 2015). Beijing's experience and lessons in the development and implementation of environmental control policies and programs can be a model for many Chinese provinces.

From the empirical results, Tianjin has the highest average industrial eco-efficiency score of 0.81 in China during the study period. As shown in Figure 1, the eco-efficiency score increased over time, except for the year 2009, and achieved 1 in 2010. This result is consistent with the fact that Tianjin pursued the policies of optimizing industrial structure, develop a green economy, strictly control pollution caused by coal combustion, establish strict environmental access mechanisms, and eliminate backward production capacity. For instance, during the 11th Five-Year Plan period (2006–2010), Tianjin has strengthened energy conservation by focusing on the energy utilization efficiency and the development of renewable energy projects such as wind, solar, and biomass power generation during these years (Tianjin Ecology and Environment Bureau, 2012). As a result, in 2010, its energy consumption per GDP became 0.826 tons of standard coal equivalent per yuan, which is 21% lower than the 2005 level and exceeded the energy-saving target of 20% reduction during the 11th Five-Year Plan period (Tianjin Ecology and Environment Bureau, 2012). In addition, it is stated that Tianjin should vigorously optimize the structure of energy consumption, promote low-carbon industries, and strictly restrict the development of energy-intensive industries. At the same time, the quality and efficiency of industrial enterprises have been improved significantly. For instance, in recent years, Tianjin has accelerated the elimination of backward production capacity and overcapacity, encouraged the energy-saving transformation of high energy-consuming enterprises, continuously improved energy utilization methods in key areas.

The great progress of industrial eco-efficiency happened not only in Beijing and Tianjin. Inner Mongolia is one of China's most important energy production bases, which has experienced remarkable socioeconomic and environmental changes during the study period. The industrial eco-efficiency scores rapidly increased to 1 in 2009 from 0.318 in 2005. This is a considerable improvement and has great significance in the development of sustainable industry. In the past, Inner Mongolia was relatively backward in economy and has developed by wasting huge resources and damaging the environment (Yang et al., 2012). Since the implementation of the western development strategy in 1999, Inner Mongolia has received a lot of investment and preferential policies from the national government. Per-capita income in Inner Mongolia grew from 5861 yuan in 1999 to 71101 yuan in 2015 (National Bureau of Statistics, 2005-2015). The achievement of economic growth also provides strong support for ecological development and the level of green development has steadily improved. During the 11th and 12th Five-Year Plans, energy consumption per unit of industrial added value decreased by 42.9% and 31.9%, respectively. The eco-industrial achievement in Inner Mongolia is exemplary for other regions in China. As discussed above, Beijing, Tianjin, Inner Mongolia have great improvement in industrial eco-efficiency. However, it should be noted that some provinces still remain low eco-efficiency in 2015. For example, Hebei has relatively low industrial eco-efficiency score (0.477) in 2015. Hebei is the province which has long been driven by the consumption of resources, the backwardness of the environmental infrastructure, and the illegal gas emission of small enterprises (Li et al., 2020). The fog and haze appear frequently and cause serious damage, which has threatened people's health and daily life work. It is stated that seven out of the top ten most polluted cities in China are located in Hebei Province in 2013 (Wang et al., 2013). Hebei was observed to have a higher industrial eco-efficiency score than Beijing in 2005, but the industrial eco-efficiency did not improve during the study period. There are several possible reasons why the industry in Hebei is not eco-efficient. First, the high proportion of heavy industry led to a large demand for energy and created large amounts of emission. The major industries in Hebei are iron, steel, coke, and cement, which have a high environmental burden (Wang et al., 2013). Second, the environmental infrastructure in Hebei is backward and there are a large number of small enterprises emitting emissions illegally (Li et al., 2020). However, it should be noted that the industrial eco-efficiency score is 1 in 2010 and then dramatically decreased in the succeeding years which indicates that the low industrial eco-efficiency in Hebei is not mainly because of the technology in a short period, but the level of regulation and enforcement.

Regarding the industrial eco-efficiency in Shanxi province, there is no improvement in the efficiency score in this province during the study period. It shows that the industrial eco-efficiency increased slowly in 2005-2011 and then decreased in the following years. Shanxi is one of the leading energy production and consumption regions in China. The total energy consumption increased from 45.55 Million tonnes of coal equivalent to 128.23 Million tonnes of coal (Zhang et al., 2019b). It seems to be one of the reasons for Shanxi's low industrial eco-efficiency because the consumption of fossil fuels is the primary source of regional air pollution and CO_2. In addition, extensive exploitation of fossil fuels results in the environmental deterioration and discharge a lot of wastewater, waste gas, and solid waste. Hence, a resource-dependent region like Shanxi should further improve the energy efficiency in industries by applying advanced energy-efficient technologies and develop non-coal industries.

The results indicate that there exist big gaps in industrial eco-efficiency among provinces even in the same regions and there is considerable potential to improve industrial eco-efficiency in many provinces. Crucially, it is necessary for the Chinese government to focus on the unbalanced eco-efficiency development of the regional industry.

3.2 Regression analysis

Using the results of DEA as a dependent variable, regression analyses are conducted to explore external factors that may have influences on the industrial eco-efficiency in China. Table 7 summarizes the results.

Table 7 Random-effects Tobit model results

Determinants	Tobit model
R&D	1.07e-08* (4.81e-09)
PSO	-0.7931893** (.2403909)
GDP	8.14e-06** (1.88e-06)
GDP^2	-3.48e-11* (1.72e-11)
IWW	1.09e-06** (3.24e-07)
IWG	-2.80e-07** (8.98e-08)
IWS	8.84e-07 (1.04e-06)
Constant	.3541229** (.0703729)

The asterisks *, ** indicate significance levels of 5%, and 1% or respectively.

The results suggest that the internal expenditure of R&D funds of industrial enterprises has a positive and statistically significant at the 5% level on the industrial eco-efficiency score, which testifies the assumption in the previous part. Previous studies have also demonstrated that technological innovation is an avenue for environmental improvement (Zhou and Zhao, 2016). However, it should be noted that R&D investment is not a result of catching up better industrial eco-efficiency but an important input to enable it (Hobday et al., 2004). Hence, the local governments should take measures to encourage and support enterprises to put considerable R&D investment and increase the investment efficiency.

Regarding the proportion of stated-owned enterprises, it was negative and statistically significant. This result can be explained by the fact that state-owned enterprises have heavy burden, lower competition, redundant workers, and poor corporate governance (Zhong, 2014, Lin et al., 2020). In China, stated-owned enterprises always enjoy more preferential policies and perform worse than other kinds of enterprises. Contrary to state-owned enterprises, private enterprises have to engage in innovation activities to maintain a competitive advantage in the market because they face tougher market legitimacy competition (Zhang et al., 2001, Liu et al., 2020). Wu (2017) also argued that private enterprises have higher innovative impetus and capabilities than state-owned enterprises. In addition, Konisky and

Teodoro (2016) suggested that private enterprises have higher environmental pressure than state-owned enterprises because they receive less protection from governments and are more likely to be penalized for environmental violations. In China, the government maintains control over the bulk of the country's resources, most of which are allocated to state-owned enterprises. The unfair allocation of the resource by the government lowers the efficiency of resource usage of state-owned enterprises. Therefore, it is essential to minimize governmental market intervention and create a competitive market environment. Furthermore, laws and regulations should not unduly discriminate between state-owned enterprises and private enterprises. Besides, privatization will bring more competition and increase the efficiency (Zhong, 2014).

In line with expectations, per capita GDP was positive and statistically significant to the industrial eco-efficiency. This is not surprising because with the development of economy, people's dissatisfaction with environmental degradation such as air, water, and waste are growing (Shi et al., 2020) and the government has to adhere to ecology first and green development to satisfy the people's increasing demands for sound environment. However, the coefficient of $(GDP)^2$ is negative, indicating an inverted U-shaped relationship between economic growth and industrial eco-efficiency.

Regarding the investment in pollution, investment in wastewater has a positive and statistically significant impact on industrial eco-efficiency, while that in solid waste was not statistically significant. A rather contradictory result is the investment in waste gas, which was negative and statistically significant on industrial eco-efficiency at the 1% level. Perhaps due to the conditions of China's current weak judicial environment, extensive corruption, and opaque investment process (Zhang et al., 2019a). It is necessary for the government to identify reasons for the negative correlation between the investment in waste gas and industrial eco-efficiency and formulate appropriate policies and strategies to improve investment efficiency.

4. Conclusion and policy implications

Based on the panel data of 30 provinces in mainland China from 2005 to 2015, this study used the two-stage approach, which first performed the DEA (SBM) model to evaluate the provincial industrial eco-efficiency score and then performed two regression methods (OLS and Tobit) to further explored the determinants. In the first stage, the results depicted that the overall trend of industrial eco-efficiency was upward. However, it should be noted that apart from several provinces (e.g., Beijing, Tianjin, Inner Mongolia, Hunan, and Guangdong), there are still many industrial technical and policy deficiencies in some regions. Most provinces are still facing low industrial eco-efficiency. In the second stage, the regression results showed that internal expenditure of R&D funds of industrial enterprises, per capita GDP and investment in wastewater have positive and statistically significant influences on provincial industrial eco-efficiency. On the contrary, the proportion of state-owned enterprises and investment in waste gas have the negative influence on provincial industrial eco-efficiency. Based on the findings of this study, the following four policy measures to improve provincial industrial eco-efficiency.

1. It is important to enhance local government official environmental performance evaluation. Although some provinces have great progress in economic development, the resources consumption and pollution still remain at high level. This can be explained by the fact that some local governments do not pay enough attention to environmental protection because the evaluation process for officials is closely linked to economic achievement, but not environmental performance (REF). Enhancing local government official environmental performance evaluation will encourage the local government to make a good balance between economy, environment and resolutely reduce energy-based and resource-based enterprises with high pollution (Pan et al., 2019). Additionally, the government should enhance the technology transfer and application from the efficient regions to the low industrial eco-efficiency regions and strengthen the coordinated development. For instance, making technical education available on a wider scale and training technicians and engineers.
2. The local government should encourage enterprises for their R&D investment. The regression analysis results show that R&D investment has a positive influence on industrial eco-efficiency. The previous study indicated that the subsidies from government will lead the enterprises to put

more R&D investment to develop environmental protection technology (Wu, 2017). Hence, the local government should provide more subsidies to enterprises that have higher innovative impetus but insufficient innovative resources, especially for private enterprises (Shi et al., 2020). In addition, it is important to increase the investment in wastewater, and more crucially, government authorities need to closely control and manage the project of governmental investment effectively to ensure investment efficiency of solid waste and waste gas and avoid wasteful resource allocation,

3. The Chinese government should consider not only the state-owned business but also the whole economy and create a circumstance for equal competition for all sorts of business. This study indicated that state-owned enterprises appears to have a negative impact on regional industrial eco-efficiency. It is imperative to restructure state-owned enterprises, encourage the private sector and reforming capital, labor and energy markets.
4. It is crucial for the central government to improve the construction of the legal system and enhance the law enforcement to ensure the effective implementation of the environmental laws and regulations. For instance, it is found that the anti-corruption policy has a significant positive influence on the investment efficiency of government-subsidized enterprises (Zhang et al., 2019a). Hence, It is imperative to enhance anti-corruption campaign because corruption has negative impacts on air pollution emissions by directly reducing the stringency of environmental regulations (Cole, 2007). Cole (2007) also noted that it is a common idea amongst enterprisers that public officials can be ‘bought’ for a fee possible to be less than the cost of obeying environmental regulations. China still has a low illegal cost and asymmetric information in environmental regulation at present. Hence, increasing punishment of illegal acts, normalizing information disclosure, and improving regulatory capacity will help to improve environmental protection. At the same time, it is necessary to implement the “zero tolerance” pollution prevention and control regulations, attach importance to environmental protection, and enhance the punishment for pollution (Shi et al., 2020).

Through the above policy recommendations, this paper offers a beneficial reference for provinces with low industrial eco-efficiency to pursue high-quality and green development.

Acknowledgements

Foremost, I would like to express my sincere gratitude to my advisor Prof. Ken'ichi Matsumoto for the continuous support of my study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. Without his guidance, I would not have been able to complete my dissertation. Secondly, I would also like to thank my two associate supervisors, Prof. Yuki Yamamoto and Prof. Yosuke Shigetomi, who also provided a lot of support for my thesis. Also, I want to thank the help from Lisa and other friends in the laboratory.

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