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Decline of net SO_2 emission intensity in China's thermal power generation: Decomposition and attribution analysis

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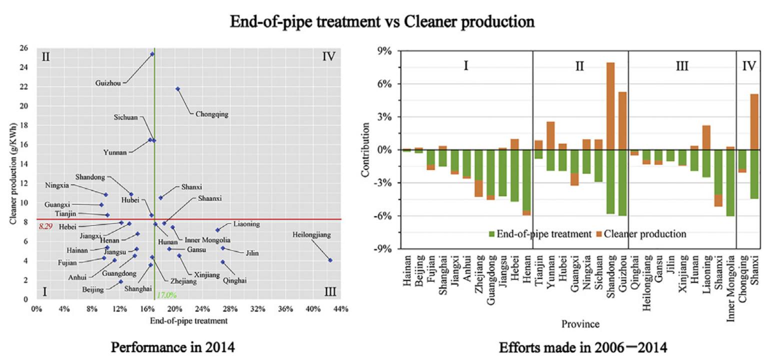
HIGHLIGHTS

- End-of-pipe treatment remained the primary way to control SO_2 pollution.
- Cleaner production exhibited a large potential in SO_2 mitigation.
- North provinces exerted more efforts in SO_2 treatment and coal intensity effects.
- South provinces made more efforts in decreasing SO_2 production factor of coal.
- Provinces were classified into 4 categories to choose targeted policy methods.

GRAPHICAL ABSTRACT



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ABSTRACT

Thermal power generation is the main electricity source of China, but also contributes the largest share of air pollutants in the country. Because of China's considerable efforts in pollution control, one measure of the most important source of air pollution net SO_2 emission intensity (*NSEI*) of thermal power generation has dropped significantly since 2006. Understanding the reasons behind the decline could help further explore the solution-space for deeper mitigation targets. This study combines multiplicative LMDI with attribution analysis to decompose the decline in national *NSEI* into four factors (i.e. SO_2 treatment or end-of-pipe approaches; SO_2 emission factor of coal and coal intensity, which both account for cleaner production measures; and geographical structure effects) for 30 regions. Our results show that end-of-pipe technologies remained the primary way to control air pollution in China. In addition, cleaner production efforts contributed to SO_2 mitigation. Attribution results at the province level show that northern provinces increased their efforts in SO_2 treatment and reducing coal intensity, while southern provinces have done more on reducing the SO_2 intensity of coal. Provinces were classified into four categories (i.e. leading regions, end-of-pipe dependent regions, process-dependent regions and lagging regions) according to their performance in terms of end-of-pipe treatment and cleaner production, to help them choose targeted policy methods.

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1. Introduction

China has been the world's largest power generator since 2011 (IEA, 2013). As its largest component, thermal power generation comprised 72% of China's total electricity capacity in 2016 (NBS, 2017). China's coal production is about half of that across the world (IEA, 2018) and nearly 50% of the coal resources is consumed for power generation (NBS, 2017). The huge amount of coal combustion unavoidably emits a large amount of air pollutants such as SO_2 emissions. SO_2 is known to cause serious environmental issues such as acid rain and fog-haze, and frequent SO_2 exposure can induce cardiovascular and respiratory diseases, bringing serious damage to human health. The thermal power industry contributed to >34% of national industrial SO_2 emissions in 2015 (MEE, 2017), making it the single greatest contributor in the country. Therefore, this sector should be considered as priority for SO_2 emissions reduction.

Since China's accession into the World Trade Organization (WTO) at the end of 2001, the electricity demand from the booming manufacturing industry rapidly drove up net SO_2 emissions (SO_2 emissions after removal) from thermal power generation, with an increase of 77% between 2001 and 2006 (Fig. 1, orange curve). Faced with increasingly severe air pollution, the Chinese government began to implement a mandatory emissions control system to reduce SO_2 emission levels. The national goal of reducing SO_2 emissions by 10% was set in the 11th Five Year Plan (FYP) period (SCC, 2008). With considerable effort in shutting down small thermal power units and installing desulfurization facilities, emissions from thermal power generation were reduced by 3.2 Mt. in this period. The Chinese government set a reduction goal of 8% in the 12th FYP period (SCC, 2011) and a reduction of 2.9 Mt. was achieved by the end of 2014. Emissions dropped by 55% from 2006 to 2014 (Fig. 1, blue curve). Meanwhile, the net SO_2 emission intensity (*NSEI*) also experienced an accelerated rate of decline in this period and a drop of 75% was achieved (Fig. 1, green curve). Understanding the reasons behind the decline could help further explore the solution-space for a deeper mitigation target to reduce SO_2 emission level by 15% in the 13th FYP period (SCC, 2016).

Similar to the inverted U-shaped evolutionary trend (Fig. 1, orange and blue curves), one could also hypothesize an inverted U-shaped curve relationship between electricity output and net SO_2 emissions (Fig. 2, black dashed curve), which confirms the existence of the electricity-net SO_2 emissions Environmental Kuznets Curve (EKC) in China's thermal power generation (Selden and Song, 1994; Kaufmann et al., 1998). Although investigating the EKC hypothesis could also inform the economic development vs. environmental protection dilemma (Shen, 2006; Song et al., 2008; Fodha and Zaghdoud, 2010; Fosten et al., 2012; Y. Wang et al., 2016; Y. Wang et al., 2017), it fails to tell us how to achieve the target or bring insights into the reasons behind the variation in emissions. In this regard, decomposition analysis is a popular

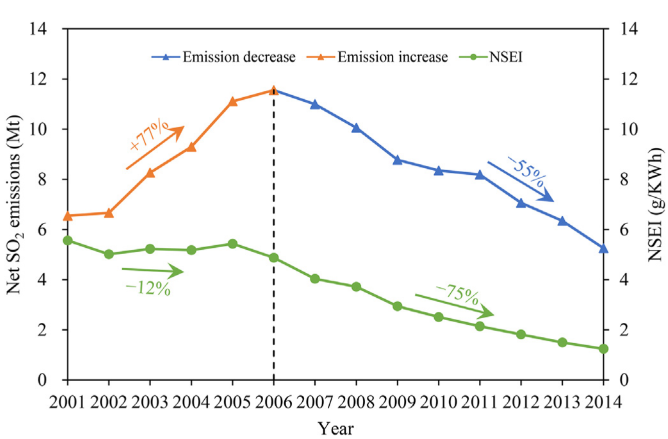

Fig. 1. Changes in net SO_2 emissions and NSEI from China's thermal power generation.

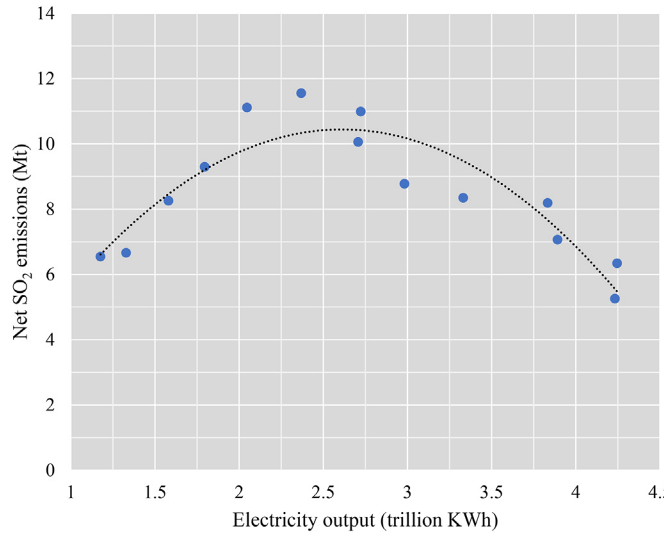

Fig. 2. Electricity-net SO_2 emissions EKC in China's thermal power generation.

technique for identifying the driving factors behind resource consumption or emissions. Wherein, structural decomposition analysis (SDA) and index decomposition analysis (IDA) are the two commonly used decomposition models (Feng et al., 2012, 2015). Compared with SDA, IDA has a lower requirement for data and is easier to apply. The literature is abundant of IDA applications to identify the determinants. Applications include energy consumption (Ang and Lee, 1994; Zhang et al., 2011; Nie and Kemp, 2014), energy intensity (Ma and Stern, 2008; Ang et al., 2015; Farajzadeh and Nematollahi, 2018; Xie and Lin, 2019), carbon emissions (Feng, 2019; Le Quéré et al., 2019) and carbon intensity (J. Wang et al., 2018; Goh et al., 2018).

As seen from Table 1, studies focusing on SO_2 emissions are abundant. For example, Liu and Wang (2013) used the LMDI technique to decompose the SO_2 emissions change of China into pollution treatment, cleaner production, spatial economic structure and trade affects. Using the same method, Yang et al. (2016) analyzed the impacts of treatment technology, energy consumption and energy structure on China's industrial SO_2 emissions between 1995 and 2014. Q.W. Wang et al. (2017) identified the factors influencing SO_2 emissions in Jiangsu and its 13 cities from a perspective of whole process treatment. Applying the whole process decomposition approach, Hang et al. (2019) decomposed industrial SO_2 emissions change in China into six specific driving factors. However, existing studies have seldom investigated the factors influencing the changes in *NSEI*, except for Zhang (2013) who used the LMDI approach to decompose the changes in province-level industrial *NSEI* into the contributions of energy structure, energy intensity, emission coefficient. Nevertheless, these studies mainly focused on regions, industrial sub-sectors or an aggregate industrial sector in China (See Table 1 for details), while SO_2 emissions from thermal power generation have rarely been addressed in the literature. In fact, the *NSEI* of thermal power generation experienced a sharp drop of 75% from 2006 to 2014 (Fig. 1, green curve). Understanding the reasons behind the decline could further help explore the solution-space for the deeper mitigation target in the 13th FYP period (SCC, 2016). In this case, it is important to perform a decomposition analysis of the decline in the *NSEI* of thermal power generation in China.

There were significant differences in SO_2 emissions between provinces between 2006 and 2014 (Fig. 3, shaded areas). Except for Xinjiang that experienced an increase of 23.7% in emissions, most provinces show a decline, of which Shanghai was found to have the largest one of over 80%. As for emission intensity, the declines between 2006 and 2014 varied significantly between provinces (Fig. 4), which implies that the reasons behind *NSEI* decline may be different. Wherein, the level of SO_2 removal is an important factor. It was found to have a

Table 1
Summary of the studies decomposing SO_2 emissions/intensity in China.

Study	Time period	Emissions/intensity	Subject	Method
He (2010)	1991–2001	Emissions	Industrial sub-sectors among regions	IDA
Liu and Wang (2013)	1995–2010	Emissions	Regions	Refined Laspeyres
Fujii et al. (2013)	1998–2009	Emissions	Industrial sub-sectors	IDA
Zhang (2013)	2001–2010	Intensity	Industrial sector as an aggregate at the province level	IDA
Yu et al. (2015)	2000–2010	Emissions	Industrial sub-sectors in Chongqing	SDA
Zhang et al. (2015)	2005–2010	Emissions	Industrial sub-sectors	SDA
Yang et al. (2016)	1995–2014	Emissions	Regions	IDA
Yao et al. (2016)	2001–2010	Emissions	Industrial sub-sectors	IDA
Liu and Wang (2017)	2005–2010	Emissions	Industrial sub-sectors	SDA
Q.W. Wang et al. (2017)	2001–2010	Emissions	Industrial sub-sectors in Jiangsu province	IDA
Hang et al. (2019)	2005–2015	Emissions	Industrial sector as an aggregate at the province level	IDA
Q. Liu et al. (2019)	2002–2010	Emissions	Provinces	SDA

significant regional disparity, with relatively low levels of removals in the northeast and northwest and high shares in the east (Fig. 3, pie chart). Thus changes in the factors influencing national *NSEI* decline need to be further investigated at the province level.

Choi and Ang (2012) proposed attribution analysis to attribute changes in driving factors to individual components, which paves the foundation for deriving differentiated policies for each region. The method combined with LMDI models has been widely applied in energy and emissions studies. Examples of such studies include energy intensity (Fernández González et al., 2013, 2015; Choi and Oh, 2014; Fernández González, 2015) and carbon intensity (Liu et al., 2015, 2017; N. Liu et al., 2019; Q.W. Wang et al., 2016; J. Wang et al., 2017; Q.W. Wang et al., 2018; Xiao et al., 2019). Especially, Hang et al. (2019) applied attribution analysis to explore contributions of end-of-pipe treatment and energy intensity effects to changes in China's industrial SO_2 emissions for various provinces. Following this spirit, the regional attribution analysis is used to reveal provincial contributions to the decline in the *NSEI* of thermal power generation in China.

This study combines multiplicative LMDI with regional attribution analysis to investigate the factors influencing the decline in *NSEI* of thermal power generation in China and attribute the contribution of each factor to different regions. This current work generates comparable decomposition and attribution results for the 11th and 12th FYP periods using data spanning the period from 2006 to 2014 across 30 regions in China and thus contributes to informing targeted SO_2 mitigation policies at the province level.

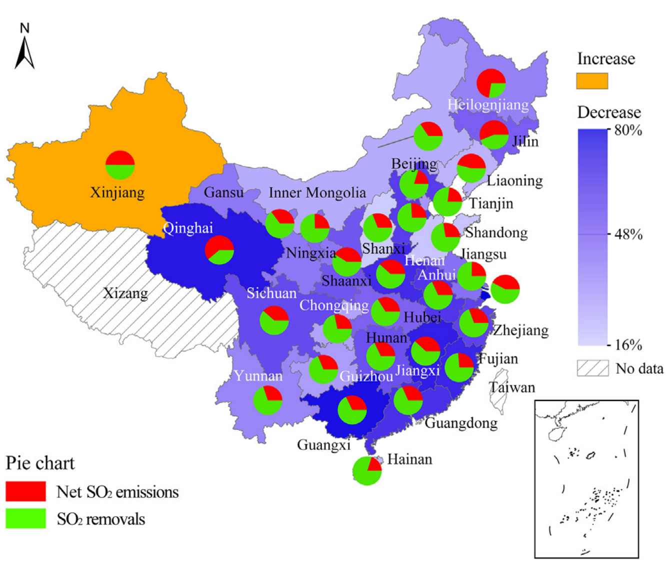

Fig. 3. Cumulative changes in net SO_2 emissions and shares of net SO_2 emissions and SO_2 removal among provinces from 2006 to 2014.

2. Methods and materials

2.1. Decomposition analysis

Following Liu and Wang (2013) and Q.W. Wang et al. (2017), the national *NSEI* of thermal power generation is typically expressed in Eq. (1).[1]

$$NSEI = \frac{NSE}{E} = \sum_{j=1}^{N} \frac{NSE_j}{SE_j}\frac{SE_j}{C_j}\frac{C_j}{E_j}\frac{E_j}{E} \tag{1}$$

where *NSE* denotes total net SO_2 emissions from thermal power generation; *E* denotes total thermal electricity output; NSE_j denotes the net SO_2 emissions of region *j*; SE_j denotes SO_2 emissions of region *j*; C_j denotes coal consumption of region *j*; E_j denotes electricity output of region *j*.

Suppose that the national *NSEI* varies from time $t-1$ to t (i.e. $NSEI^t/NSEI^{t-1}$), such a change can be expressed in the following multiplicative form as Eq. (2).

$$\begin{aligned}\frac{NSEI^t}{NSEI^{t-1}} &= \frac{\sum_{j=1}^{N}\left(NSE_j^t/SE_j^t\right)\cdot\left(SE_j^t/C_j^t\right)\cdot\left(C_j^t/E_j^t\right)\cdot\left(E_j^t/E^t\right)}{\sum_{j=1}^{N}\left(NSE_j^{t-1}/SE_j^{t-1}\right)\cdot\left(SE_j^{t-1}/C_j^{t-1}\right)\cdot\left(C_j^{t-1}/E_j^{t-1}\right)\cdot\left(E_j^{t-1}/E^{t-1}\right)}\\ &= \frac{\sum_{j=1}^{N} STL_j^t\cdot SEF_j^t\cdot CI_j^t\cdot GS_j^t}{\sum_{j=1}^{N} STL_j^{t-1}\cdot SEF_j^{t-1}\cdot CI_j^{t-1}\cdot GS_j^{t-1}}\end{aligned} \tag{2}$$

where $STL_j^t = NSE_j^t/SE_j^t$ and $STL_j^{t-1} = NSE_j^{t-1}/SE_j^{t-1}$ respectively denote SO_2 treatment level of region *j* at time *t* and $t-1$. The lower the value, the higher the treatment level is. $SEF_j^t = SE_j^t/C_j^t$ and $SEF_j^{t-1} = SE_j^{t-1}/C_j^{t-1}$ respectively denote SO_2 emission factor of coal in region *j* at time *t* and $t-1$. $CI_j^t = C_j^t/E_j^t$ and $CI_j^{t-1} = C_j^{t-1}/E_j^{t-1}$ respectively denote coal intensity of region *j* at time *t* and $t-1$, indicating energy efficiency level. The lower the value, the higher is the energy efficiency. $GS_j^t = E_j^t/E^t$ and $GS_j^{t-1} = E_j^{t-1}/E^{t-1}$ respectively denote the share of electricity output of region *j* at time *t* and $t-1$.

Eq. (2) indicates that *NSEI* change is related to four factors, such as SO_2 treatment level, SO_2 emission factor of coal, coal intensity and geographical structure of electricity output. Based on the Sato-Vartia LMDI method in multiplicative form (Ang and Choi, 1997; Ang, 2015), the decomposition results of total change in *NSEI* can be given in Eqs. (3a)–(3f).

$$D_{tot}^{t-1,t} = \frac{NSEI^t}{NSEI^{t-1}} = D_{ST}^{t-1,t}\times D_{SE}^{t-1,t}\times D_{CI}^{t-1,t}\times D_{GS}^{t-1,t} \tag{3a}$$

$$D_{ST}^{t-1,t} = \exp\left(\sum_{j=1}^{N}\omega_j^{S-V}\ \ln\frac{STL_j^t}{STL_j^{t-1}}\right) \tag{3b}$$

[1] We here assume that coal combustion is the sole source of SO_2 emissions from China's thermal power generation, as China's oil-fired power and gas-fired power both account for a tiny proportion and generate little SO_2 pollution.

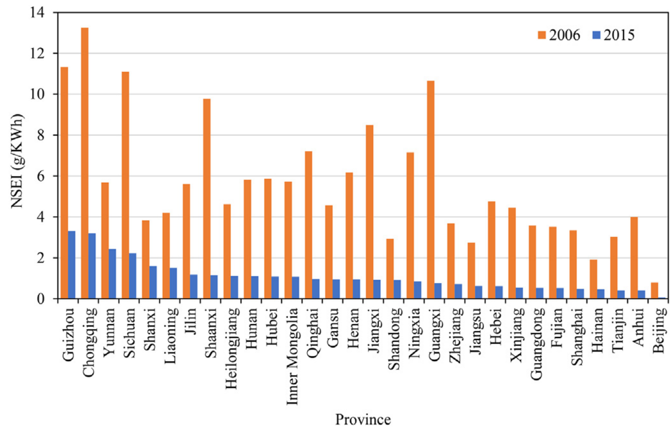

Fig. 4. NSEI of provinces in 2006 and 2014.

$$D_{SF}^{t-1,t} = \exp\left(\sum_{j=1}^{N} \omega_j^{S-V} \ln\frac{SEF_j^t}{SEF_j^{t-1}}\right) \tag{3c}$$

$$D_{CI}^{t-1,t} = \exp\left(\sum_{j=1}^{N} \omega_j^{S-V} \ln\frac{CI_j^t}{CI_j^{t-1}}\right) \tag{3d}$$

$$D_{GS}^{t-1,t} = \exp\left(\sum_{j=1}^{N} \omega_j^{S-V} \ln\frac{GS_j^t}{GS_j^{t-1}}\right) \tag{3e}$$

$$\omega_j^{S-V} = \frac{L\left(NSE_j^{t-1}/NSE^{t-1}, NSE_j^t/NSE^t\right)}{\sum_{j=1}^{N} L\left(NSE_j^{t-1}/NSE^{t-1}, NSE_j^t/NSE^t\right)} \tag{3f}$$

where $D_{ST}^{t-1,\,t}$, $D_{SF}^{t-1,\,t}$, $D_{CI}^{t-1,\,t}$ and $D_{GS}^{t-1,\,t}$ respectively measure the effects of SO_2 treatment, SO_2 emission factor of coal, coal intensity and geographical structure over the period $[t-1,t]$; ω_j^{S-V} denotes the weight of region j and $L(a,b)=(b-a)/(\ln b - \ln a)$ is the logarithmic mean function.

Eq. (3a) describes the single-period decomposition results of *NSEI* change. In the case of multi-period decomposition, the accumulative effect $D_{tot}^{0,\,T}$ from time 0 to T can be calculated by Eq. (4) (Choi and Ang, 2012).

$$\begin{aligned} D_{tot}^{0,T} &= \frac{NSEI^T}{NSEI^0} = \prod\nolimits_{t=1}^{T} \frac{NSEI^t}{NSEI^{t-1}} \\ &= \prod\nolimits_{t=1}^{T}\left(D_{ST}^{t-1,t} \times D_{SF}^{t-1,t} \times D_{CI}^{t-1,t} \times D_{GS}^{t-1,t}\right) \\ &= D_{ST}^{0,T} \times D_{SF}^{0,T} \times D_{CI}^{0,T} \times D_{GS}^{0,T} \end{aligned} \tag{4}$$

where $D_{ST}^{0,\,T}$, $D_{SF}^{0,\,T}$, $D_{CI}^{0,\,T}$ and $D_{GS}^{0,\,T}$ are the corresponding cumulative products of single-period decomposed indexes.

2.2. Regional attribution analysis

Attribution analysis is applied to further attribute changes in national *NSEI* by each factor to regions (Choi and Ang, 2012). The method has a requirement on the weights and the sum of them need to be unity. This is why we choose Sato-Vartia LMDI method other than Montgomery-Vartia to model Eqs. (3a)–(3f) (Choi and Oh, 2014). The regional attribution analysis method is given in the following by using geographic structure (GS) effect (i.e. $D_{GS}^{t-1,\,t}$). The single-period attribution results over the period $[t-1,t]$ can be expressed as Eq. (5).

$$\begin{aligned} D_{GS}^{t-1,t}-1 &= \sum_{j=1}^{N} c_{GS,j}^{t-1,t} = \sum_{j=1}^{N} r_{GS,j}^{t-1,t}\left(\frac{GS_j^t}{GS_j^{t-1}}-1\right) r_{GS,j}^{t-1,t} \\ &= \frac{\dfrac{\omega_j^{S-V}}{L\left(GS_j^{t-1}D_{GS}^{t-1,t}, GS_j^t\right)} GS_j^{t-1}}{\sum_{j=1}^{N} \dfrac{\omega_j^{S-V}}{L\left(GS_j^{t-1}D_{GS}^{t-1,t}, GS_j^t\right)} GS_j^{t-1}} \end{aligned} \tag{5}$$

where $c_{GS,j}^{t-1,\,t}$ denotes the contribution of region j to the GS effect; $r_{GS,j}^{t-1,\,t}$ is the weight of region j, and measures its impact of on the GS effect. Eq. (5) indicates that the single-period percent change of GS effect can be further attributed to provinces.

We can further derive the multi-period attribution analysis from the single-period attribution results. The multi-period contribution of the region j to the change in the GS effect over the period $[0,T]$ can be described in Eq. (6).

$$D_{GS}^{0,T}-1 = \sum_{j=1}^{N} c_{GS,j}^{0,T} = \sum_{j=1}^{N}\sum_{t=1}^{T} D_{GS}^{0,t-1} c_{GS,j}^{t-1,t} \tag{6}$$

where the item $c_{GS,j}^{0,T} = \sum_{t=1}^{T} D_{GS}^{0,t-1} c_{GS,j}^{t-1,t}$ denotes the multi-period contribution of region j to the GS effect. Analogs to the foregoing derivations described as Eqs. (5) and (6), we can also obtain the contribution of each region to the changes of the other three effects.

2.3. Date sources

The data for SO_2 emissions and SO_2 removals from thermal power generation across 30 provincial administration regions (hereafter denoted as provinces for short) in China from 2006 to 2014 were obtained from Annual Statistic Report on Environment in China (2006–2014). The data for thermal power generation capacity and coal consumption across 30 provinces from 2006 to 2014 were collected from China Energy Statistical Yearbook (2007–2015).

3. Results and discussions

3.1. Decomposition analysis

Eqs. (3a)–(3f) and (4) were used to decompose the changes in the national *NSEI* of thermal power generation from 2006 to 2014 (Fig. 5 and Table S1). The trend of SO_2 treatment effect (D_{ST}) was close to the

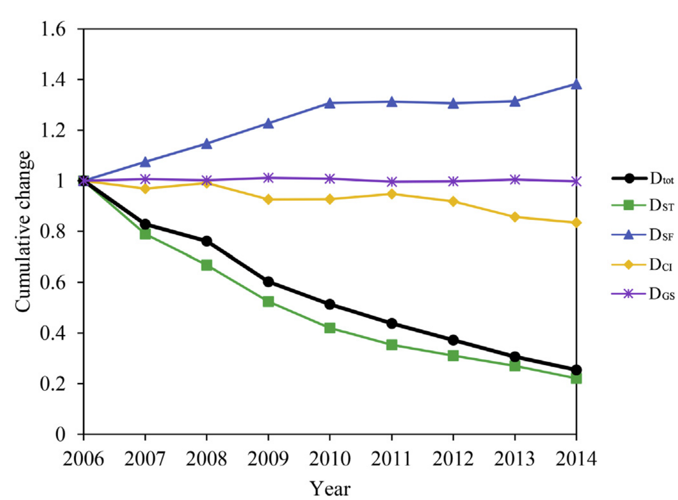

Fig. 5. The trends of cumulative changes in the national NSEI and its decomposition.

trend associated with *NSEI* (Fig. 5, green and black curves), indicating its leading role in promoting *NSEI* decline. It was found to cause cumulative reductions of 58.0%, 37.5% and 77.9% in the periods 2006–2010, 2011–2014 and 2006–2014, respectively (Table S1). From 2006 to 2011, SO_2 removals experienced a sharp increase by 487%, largely mitigating emissions in this period (Fig. 6, green area). China has combined mandatory measures with subsidy policies to vigorously promote coal-fired power plants to install desulphurization facilities in this period. The proportion of plants installed with desulphurization systems grew from 12% in 2005 to 83% in 2010 and then reached 99% by the end of 2015 (SCC, 2011, 2016). This demonstrates China's considerable efforts in the end-of-pipe treatment of SO_2 pollution for the thermal power industry.

Coal intensity (D_{CI}) was another important factor contributing to decreasing the *NSEI* (Fig. 5, yellow curve). Its cumulative effect for the whole period was −16.6% (Table S1). This is mainly due to improvement in energy utilization efficiency in thermal power generation, which was achieved by shutting down small coal-fired power units. Units of 300 MW and above accounted for 79% and the coal consumption of per KWh electricity generation decreased to 312 g by the end of 2016 (SCC, 2017). In comparison, the SO_2 emission factor effect (D_{SF}) showed a significant increase resulting in an increase of the *NSEI* by 38.4% for the study period (Fig. 5, blue curve). This may be partly explained by the continuous decline of coal-washing rate in thermal power generation (Fig. 7, green curve). The coal-washing rate was found to decrease by 38.3% from 1.83% in 2006 to 1.13% in 2014. This trend slowed noticeably after 2011. As a result, the increasing effect of SO_2 emission factor also decreased from 30.8% for the 2006–2010 period to 5.4% for the 2011–2014 period (Fig. 5, blue curve). The geographical structure effect (D_{GS}) was found to fluctuate around 1 (Fig. 5, purple curve), indicating relatively minor impacts on *NSEI* change.

Thermal electricity output has continued to increase over the entire period, but at a decelerated rate after 2011 (Fig. 8, purple curve). Correspondingly, SO_2 emissions experienced a continuous increase by 106% between 2006 and 2011, but plateaued after 2011 (Fig. 6, blue curve). This is mainly because the demand for electricity was partially fulfilled by other electricity sources such as hydropower, wind power and nuclear power. The ratio of electricity generation from clean energy sources has witnessed a significant increase since 2011, and it even reached 24.1% by 2016 (See Fig. S1 for details). SO_2 emission intensity (*SEI*) denotes SO_2 emissions per unit of electricity output. It equals the product of SO_2 emission factor and coal intensity. As such, the *SEI* here

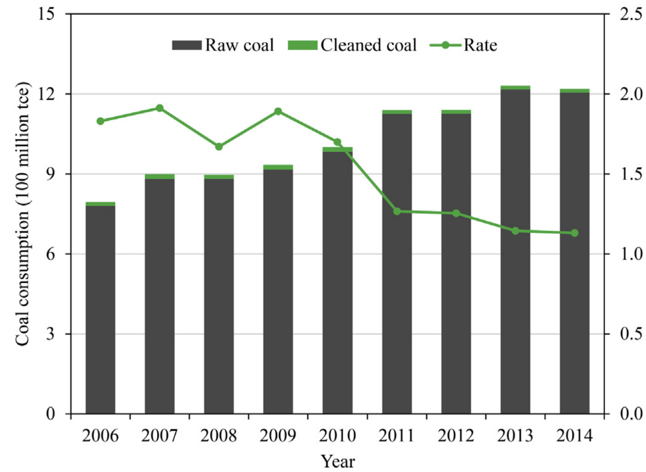

Fig. 7. Coal components and coal-washing rate in thermal power generation.

can denote the cleaner production level of thermal power, since cleaner production aims to generate the same quantity of electricity with less energy inputs and fewer pollutants (Liu and Wang, 2013). The effects of coal intensity and SO_2 emission factor here can be collectively referred to as the cleaner production effect which is a process-based treatment effect corresponding to the end-of-pipe treatment (i.e. SO_2 treatment effect). From 2006 to 2014, *SEI* showed an inverse U-curve with a peak in 2011 (Fig. 7, orange curve). This demonstrates the growing impact of cleaner production on decreasing *NSEI* in the 12th FYP period (Fig. 5, yellow and blue curves).

3.2. Regional attribution analysis

Table S2 indicates the single-period attribution results of the SO_2 treatment effect. This factor drove down *NSEI* in every year with an annual average reduction rate of 17.13%. Provinces such as Shandong (−1.42%), Henan (−1.30%), Inner Mongolia (−1.25%), Guizhou (−1.18%) and Shanxi (−1.04%) contributed the most (Table S2), due to their large capacity of power generation with high pollution intensity and popularization of disulphurization facilities for SO_2 emission reduction. Table S3 indicates the single-period attribution results of the coal intensity effect. It can be observed that this factor brought down *NSEI*

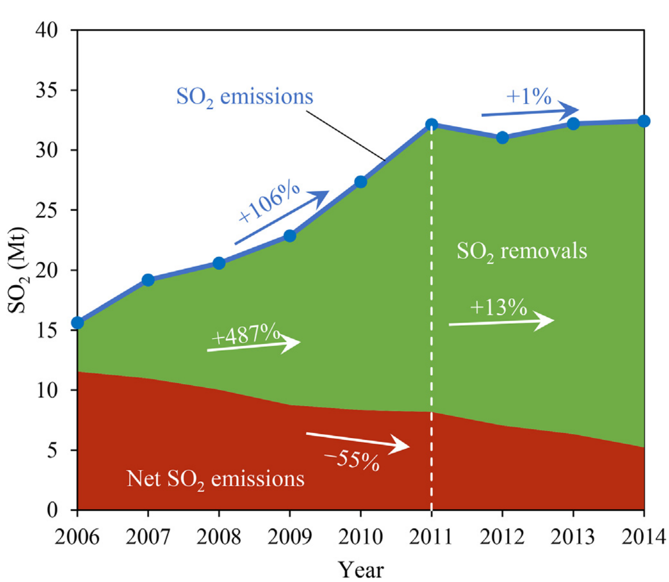

Fig. 6. Trends of net SO_2 emissions, SO_2 removals and SO_2 emissions from China's thermal power industry.

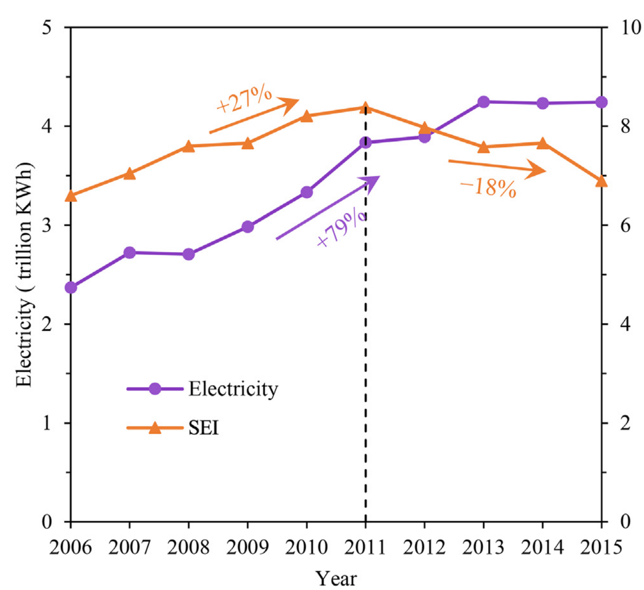

Fig. 8. Trends of electricity output and SEI of China's thermal power industry.

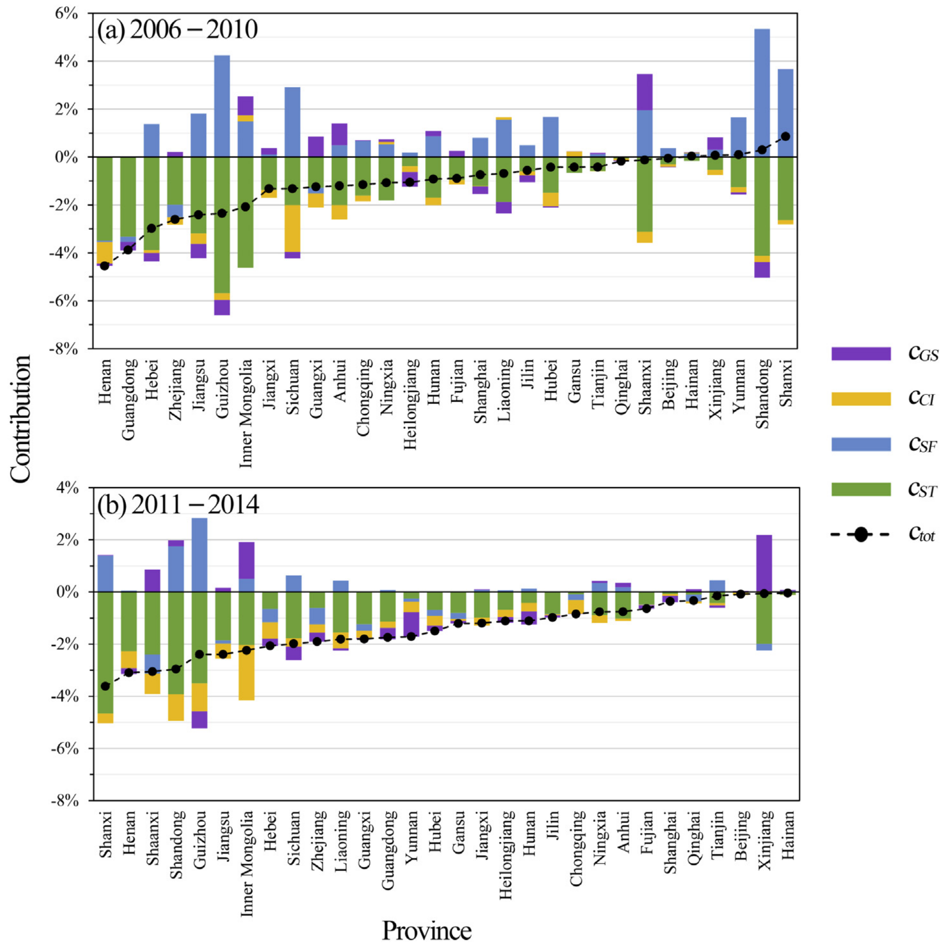

Fig. 9. Provincial total contribution and its components in different periods.

in most years, except for three periods in the 11th FYP when modest increases occurred. Inner Mongolia, Shandong, Hebei and Guizhou were primarily responsible for these short-term increases. Due to the rapidly increasing electricity demand, environmental measures like shutting down small coal-fired power plants were not strictly implemented in these regions to control the coal intensity. Nonetheless, over the entire period, the coal intensity effect decreased the *NSEI* by 2.18% annually. Table S4 indicates the single-period attribution results of the effect of SO_2 emission factor increasing the *NSEI* in most years with an annual average rate of 4.19%. Shandong (1.00%), Guizhou (0.63%) and Shanxi (0.58%) contributed the most to the increase, while southern provinces like Zhejiang, Fujian and Guangxi made a negative contribution.

Fig. 9 shows the multi-period attribution results in terms of provincial total contributions and its components for the periods 2006–2010 and 2011–2014. By comparing the two figures, we can see that in the latter period all provinces show *NSEI* decline (Fig. 9, black dashed curve). This is related to the abatement of SO_2 emission factor effect on increasing *NSEI* and the coal intensity effect decreasing *NSEI* in most provinces (Fig. 9, blue and yellow bars). Particularly, provinces such as Shanxi, Shandong and Shaanxi witnessed a big boost in terms of the rankings in total contribution, which demonstrates their efforts in SO_2 mitigation. With regards to geographical structure effect, Xinjiang, Inner Mongolia, Anhui and Shaanxi made relatively significant contributions resulting in upward influence on the *NSEI* (Fig. 9, purple bar). This means their share of thermal power generation in the country increased which may be attributed to increases in electricity demand and their rich coal reserves (See Figs. S2 and S3 for details). Also, the correlation analysis reveals that the geographical shift of thermal power generation was found to have a significant correlation with the changes in electricity demand (Table S5, $p = 0.000 < 0.01$, Pearson's $r = 0.739$) and coal production (Table S6, $p = 0.000 < 0.01$, Pearson's $r = 0.744$). Therefore, electricity demand and coal resources endowment are the main reasons behind the geographical shift in thermal electricity generation.

3.3. Cleaner production vs. end-of-pipe treatment

Fig. 10 compares the performance of 30 provinces in terms of cleaner production and end-of-pipe treatment in 2014.[2] The figure is divided into four areas by the two average lines to classify the 30 provinces into four categories. Fig. 11 indicates the regional attribution results of cleaner production and end-of-pipe treatment effects between 2006 and 2014.[3] This figure is also divided into four areas corresponding to the classification of 30 provinces in Fig. 10.

As shown in Fig. 10, provinces like Hainan, Beijing, Fujian, Shanghai, Jiangxi, Anhui, Zhejiang, Guangdong, Jiangsu, Hebei and Henan in Area I are referred to as “leading regions” in SO_2 pollution control, since these provinces perform well in terms of cleaner production and end-of-pipe treatment. These provinces had a relatively minor contribution of

[2] The end-of-pipe treatment level corresponds to the SO_2 treatment level defined in Section 2, and the cleaner production level is denoted by the SEI. For the both two, the lower value is, the higher level is.

[3] As the cleaner production effect consists of coal intensity and SO_2 emission factor effects, the contribution of a province to cleaner production equals to the sum of its contributions to the two factors.

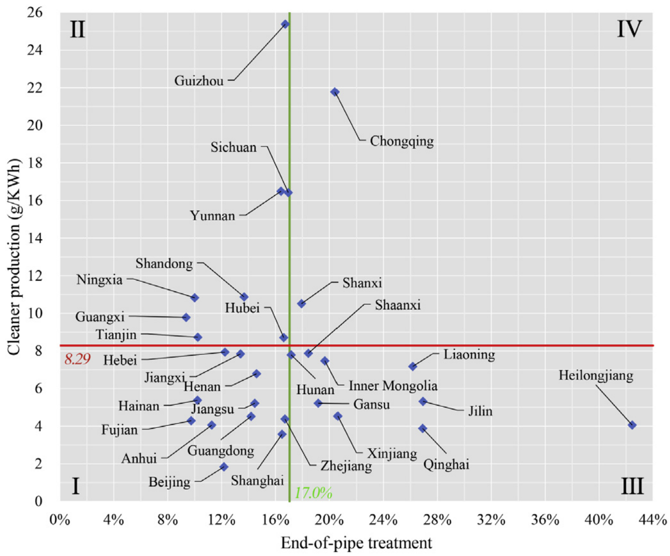

Fig. 10. Performance matrix based on cleaner production and end-of-pipe treatment levels in 2014.

cleaner production (Fig. 11, area I, orange bar). However, the contributions of end-of-pipe treatment varied considerably. Hainan, Beijing, Fujian and Shanghai contributed less while Jiangxi, Anhui, Zhejiang, Guangdong, Jiangsu, Hebei and Henan had a bigger contribution (Fig. 11, area I, green bar). In fact, the former regions had done a good job in end-of-pipe treatment before 2006, while the latter provinces witnessed a significant progress made in the desulphurization of coal-fired power plants during the period 2006–2014, showing a larger contribution of the end-of-pipe treatment (Zhang, 2013).

With regards to Area II, Tianjin, Yunnan, Hubei, Guangxi, Ningxia, Sichuan, Shandong and Guizhou can be referred to as “end-of-pipe dependent regions” in SO_2 pollution control, since process treatment (i.e. cleaner production) is below the average level and pollutant control mainly relies on end-of-pipe treatment in these regions. Except for Guangxi, the other seven provinces all had a positive contribution of the cleaner production effect (Fig. 11, area II, orange bar), indicating they were taking the “pollute first, treat later” road and neglected the way of controlling pollution from the source. Particularly, Shandong was found to have the highest contribution, which may be attributed to its large consumption of coal (accounting for 8.6% of the total in China) and its dense distribution of coal-fired plants (Xiong et al., 2016). For Yunnan, Guizhou and Sichuan, this is also related to technological laggard position and their widespread use of high-sulfur coal (Zhao et al., 2008).

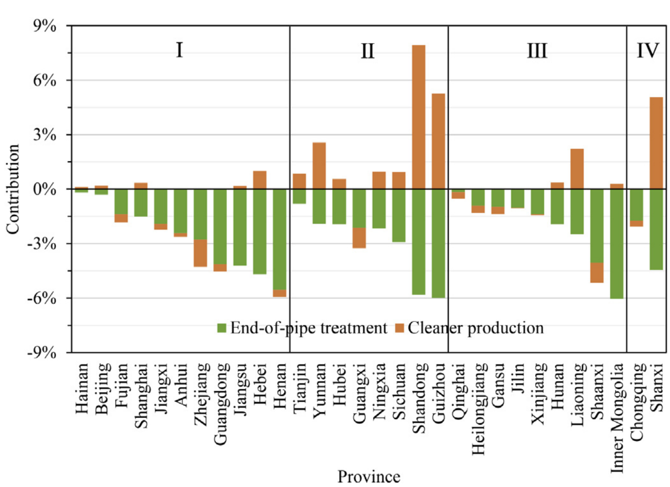

Fig. 11. Regional attribution results of cleaner production and end-of-pipe treatment effects in 2006–2014.

Provinces such as Qinghai, Heilongjiang, Gansu, Jilin, Xinjiang, Hunan, Liaoning, Shaanxi and Inner Mongolia in Area III can be referred to as “process-dependent regions”, since cleaner production is better than average, but end-of-pipe treatment needs to be improved in these regions. Hunan, Liaoning, Shaanxi and Inner Mongolia were found to contribute significantly to the end-of-pipe treatment effect (Fig. 11, area III, green bar). This demonstrates their efforts in improving the end-of-pipe treatment level of power plants, but the work should still be pushed forward in depth, especially for the remaining provinces like Qinghai, Heilongjiang, Gansu, Jilin and Xinjiang which had a relatively minor contribution (Hang et al., 2019).

Finally, Chongqing and Shanxi in Area IV are called as “lagging regions”, since they perform poorly in both effects. Shanxi was found to contribute significantly to end-of-pipe treatment effect, while Chongqing had a much minor contribution (Fig. 11, area IV, green bar). However, in terms of cleaner production, Chongqing was found to make much more efforts than Shanxi (Fig. 11, area IV, orange bar). This may be due to the local government of Chongqing implementing regulations set by the central government to promote cleaner production in their industries since 2003 (Yu et al., 2015).

4. Conclusion and policy implications

This study combined multiplicative LMDI with attribution analysis to decompose the decline in *NSEI* of China's thermal power generation into four specific factors and quantify the contributions of different provinces. Several key findings are summarized in the following.

First, China's SO_2 pollution control effort for thermal power generation has not broken away from the “pollute first, treat later” approach. End-of-pipe treatment remained the primary way to control air pollution, since SO_2 treatment effect was the dominant factor in decreasing *NSEI*. However, cleaner production shows significant potential for SO_2 mitigation, as the SO_2 emission factor effect on increasing *NSEI* got weaker while coal intensity effect on declining *NSEI* asserted a stronger impact.

Second, regional attribution results show that northern provinces have exerted more efforts in SO_2 treatment and coal intensity effects, while southern provinces have done more in SO_2 emission factor of coal. This is related to the regional disparity in terms of economic development, resource endowment and environmental regulations. Provinces were classified into four categories (i.e. leading regions, end-of-pipe dependent regions, process-dependent regions and lagging regions) according to their performance in terms of cleaner production and end-of-pipe treatment. Combined with corresponding regional attribution results, this can help inform targeted policies for each province.

In the “leading regions” (Area I), for developed provinces such as Beijing and Shanghai, measures such as developing clean coal technology and ultra-supercritical power generation technology should be promoted to achieve further mitigation potential of cleaner production. For the other provinces in this category such as Jiangxi, Anhui, Henan, and Hebei, further improvement of end-of-pipe technologies are suggested.

For the provinces in “end-of-pipe dependent regions” (Area II), measures such as shutting down of small coal-fired power plants should be encouraged to improve cleaner production. In addition, provinces such as Yunnan, Guizhou and Sichuan can further reduce the sulfur content of coal by widespread use of coal washing and similar approaches. Additionally, as for the policy measures on SO_2 treatment, Shandong and Guizhou could maintain their current policy strength, but for other provinces like Tianjin, Yunnan, Hubei, Guangxi and Ningxia, the relevant policies should be strengthened to further improve the end-of-pipe treatment level.

In the “process-dependent regions” (Area III), except for Inner Mongolia and Shaanxi that maintained end-of-pipe approaches, the other provinces such as Qinghai, Heilongjiang, Gansu, Jilin, Xinjiang, Hunan and Liaoning should push forward to further improve the SO_2 treatment level. On the other hand, policies such as shutting down small coal-fired power units and incentivising coal preparation technology are recommended especially for Liaoning, Hunan and Inner Mongolia.

In end-of-pipe dependent regions” (Area IV), Shanxi should maintain its policy in end-of-pipe treatment, but Chongqing should make more efforts in this regard by further popularizing desulphurization systems in power plants. In addition, Shanxi is also faced with an urgent need to improve cleaner production. So, policies such as shutting down small coal-fired power units and incentivising coal preparation technologies should be further pushed.

Finally, environmental subsidies would help fund power firms to upgrade their desulfurization technologies, eliminate outdated production technologies, and apply coal cleaning technologies. Also, greater inter-provincial cooperation and support is strongly recommended to promote technology transfer and achieve the early adoption of power plants with higher efficiency. In step with local resources and economic conditions, further incentives for replacing thermal power with hydro, solar, wind and nuclear power are needed. A balanced and coordinated electricity generation system could not only fulfill power demands but also reduce air pollution emissions.

CRediT authorship contribution statement

Zhencheng Xing: Conceptualization, Investigation, Writing - original draft. **Jigan Wang:** Data curation, Funding acquisition, Writing - review & editing. **Kuishuang Feng:** Supervision, Methodology, Validation, Writing - review & editing. **Klaus Hubacek:** Project administration, 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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Appendix A. Supplementary data

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