

Article

The Effects of Coal Switching and Improvements in Electricity Production Efficiency and Consumption on CO₂ Mitigation Goals in China

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Abstract: Although the average CO₂ emission for a person in China is only about 1/4 that of a person in the US, the government of China still made a commitment to ensure that CO₂ emissions will reach their peak in 2030 because of the ever-increasing pressure of global warming. In this work, we examined the effects of coal switching, efficiency improvements in thermal power generation and the electricity consumption of economic activities on realizing this goal. An improved STIRPAT model was developed to create the scenarios. In order to make the estimated elasticities more consistent with different variables selected to construct the formulation, a double-layer STIRPAT model was constructed, and by integrating the two equations obtained by regressing the series in each layer, we finally got the equation to describe the long-run relationship among CO₂ emissions (I_c), the share of coal in overall energy consumption (FM_c), coal intensity of thermal power generation (CI_p) and electricity intensity of GDP (EI_{elec}). The long term elasticities represented by the equation show that the growth of CO₂ emissions in China is quite sensitive to FM_c , CI_p and EI_{elec} . After that, five scenarios were developed in order to examine the effects of China's possible different CO₂ emission reduction policies, focusing on improving FM_c , CI_p and EI_{elec} respectively. Through a rigorous analysis, we found that in order to realize the committed CO₂ emissions mitigating goal, China should obviously accelerate the pace in switching from coal to low carbon fuels, coupled with a consistent improvement in electricity

efficiency of economic activities and a slightly slower improvement in the coal efficiency of thermal power generation.

Keywords: coal switching; coal intensity of thermal power generation; electricity intensity of GDP; renewable energies; STIRPAT

1. Introduction

Coal consumption and electricity production contribute significantly to environmental change and CO₂ emissions worldwide, which are considered the major sources of global warming. This is especially true in China. As estimated by the IEA [1], the world emitted a total of 31,734 million tons of CO₂ through fuel combustion in 2012, while China emitted 8250.8 million tons, accounting for 26.00% of the world total. The statistics also show that China replaced the United States as the world's largest CO₂-emitting country in 2006. Because of this huge volume of CO₂ emissions, China faced great pressure to reduce CO₂ emissions both to slow down the worldwide warming trend and for domestic economic sustainability. Although the average CO₂ emission for a person in China is only about 1/4 that in the US, the Chinese government still promised that China will make its biggest effort to mitigate CO₂ emissions, and that they will peak in the year 2030.

This is a huge promise and also a major challenge for China, and there have been criticisms from some researchers and experts saying that the goal is too ambitious to achieve. However, there are many opportunities for China to reduce CO₂ emissions, with reducing the share of coal in overall energy consumption being well-recognized as one of the most necessary ways [2,3]. Because of its carbon-intensive attributes, coal has been abandoned by many developed countries as a main fuel source in order to reduce greenhouse gas (GHG) emissions; however, in China, coal has supported more than 70% of overall energy consumption and this situation does not seem to have improved very much during last 30 years or more. It is therefore very possible for China to reduce coal consumption and increase the use of other, low-carbon fuels like renewable energy, nuclear power, biomass energy and natural gas, thus slowing down the growth of CO₂ emissions. Besides coal switching, improvements in energy efficiency of electricity production and consumption are also very crucial for reducing China's CO₂ emissions. That is mainly because power generation consumed more than 50% of China's coal resources (Figure 1) and is also the largest CO₂ emitting sector in China, contributing to more than 30% of China's overall CO₂ emissions (Figure 2). As a result of this China has made the improvement of coal efficiency of thermal power generation a national priority for reducing GHG emissions [4]. Moreover, improvement in efficiency of electricity consumption is also important for China to mitigate CO₂ emissions [5].

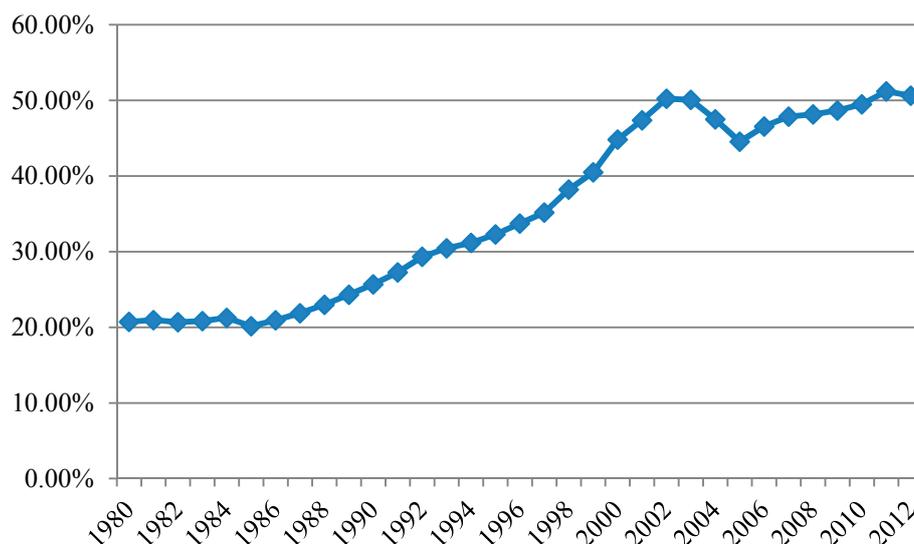


Figure 1. Proportion of coal used by electric power generation in China from 1980 to 2013. Data source: self-calculated and collected from *China Energy Statistical Yearbook* 1986, 1991, 1996, 1999, 2004–2013 [6–11].

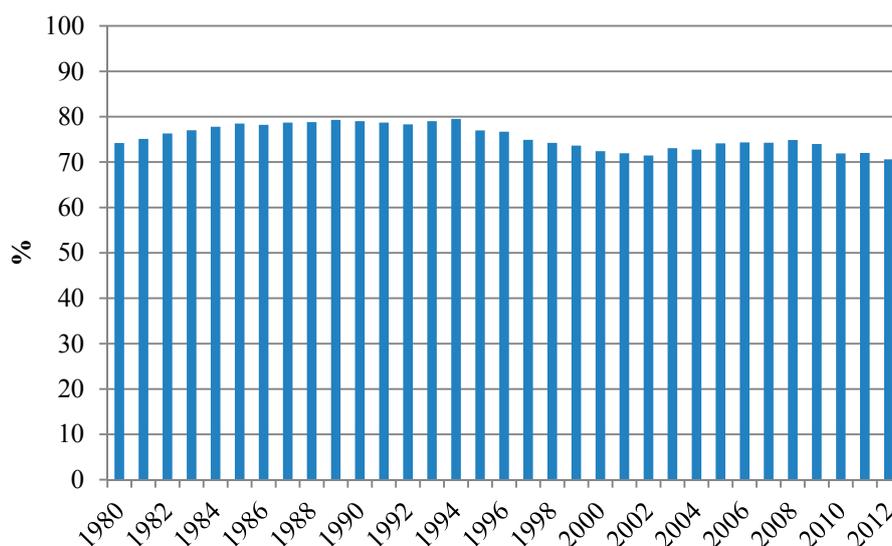


Figure 2. The contribution of power generation in overall CO₂ emissions in China from 1980 to 2012. Data sources: data on energy consumption was self-collected from *China Energy Statistical Yearbook* 1986, 1991, 1996, 1999, 2004–2013 [6–11], data on CO₂ was estimated by multiplying the CO₂ emission factor [12] and consumption of different kinds of energy.

Obviously, coal switching and energy efficiency improvement in electricity production and consumption have great potential for reducing CO₂ emissions in China, but it is very important for policy makers to know the extent to which improving these factors can help achieve the CO₂ emissions mitigation goal in 2030. The first important thing that needs to be known is the relationship between these factors and CO₂ emissions. There are many studies that deal with the relationship between CO₂ emissions and fuel switching. Özbuğday's [13] research shows that substituting renewable energy for

non-renewable energy reduces CO₂ emissions in the long run. Jorges [14] finds that an increase in the share of water heating and electric appliances has an effect on reducing household energy consumption and thus CO₂ emissions in Mexico's residential sector. In Luciano's [15] research, the diversification of the energy mix towards cleaner sources is found to be the main factor contributing to emission mitigation in Brazil. Similar research was also done in China. Geng [16] takes Liaoning Province in China as an example to investigate the different factors that contribute to the increase of CO₂ emissions, the findings show that improvement in energy intensity and fuel switching can partly offset the CO₂ emission increase caused by other factors such as growth in population and energy consumption per capita. In Yuan's [17] research, it is found that fuel switching can reduce indirect emissions of CO₂ emissions in the residential sector of all regions in China, which is consistent with the researches of Ouyang [18], Wang [19] and Wang [20] with analyses on different sectors and regions in China. All of these studies confirm the positive role of diversification of the energy mix toward low carbon fuels in contributing to the reduction of CO₂ emission; however, the effects vary greatly depending on the countries, regions, sectors and economic developing levels researched. Also, because China's energy consumption is dominated by coal and as pointed out by Lin [21], the share of coal in the total energy consumption is highly negatively related to the CO₂ performance in China, reducing the coal share of final energy consumption is among the first priorities in diversifying the energy mix toward low carbon fuels, like renewable energy, nuclear power, biomass fuels or natural gas. Regarding the roles of energy efficiency improvements in electricity production and consumption contributing to mitigating CO₂ emissions, there are also many studies. However, most of them just focus on the contribution of the electric power sector to CO₂ emissions, as found in [22–26] and also some specific research in China, like in [27,28]. Generally speaking, the results of this research show that improvements in energy efficiency in power generation, especially by integrating more renewable energy into the power sector, are important to reduce the CO₂ emissions of electricity production. Still other researchers study the improvement of power generation energy efficiency in contributing to reducing the overall CO₂ emissions for all sectors. These can be found in Sahbi [29] and Odenberger [30]. Although, as pointed out by Odenberger [30], integrating more renewable energy into power generation is crucial for the UK to achieve its goal of 60% reduction in CO₂ by 2050 compared to 1990, Sahbi [29]'s research shows that for fossil fuel-intensive power generation (like China), to improve the energy efficiency of fossil fuel power generation and electricity consumption are more important than to increase the share of renewable energies in mitigating all sectors' CO₂ emissions.

Although there are many studies dealing with the effects of each or some of the factors, including fuel switching, energy efficiency improvement of electricity production and consumption, in contributing to the CO₂ emissions mitigation, there is limited evidence available with regard to putting them together to employ their aggregate effects on mitigating CO₂ emissions in China, and this is exactly the main contribution of this work. This work also contributes a double-layer STIRPAT model that was developed in order to make the estimation of long-term elasticities more consistent no matter what factors were selected, to reflect the technologies' effects on CO₂ emission. Based on that contribution, the long-term elasticities of coal switching, energy efficiency improvement in thermal power generation and electricity efficiency of economic activities were estimated, which further guided the development of five scenarios used to trace the trend of CO₂ emissions. Through a rigorous scenario analysis, the reference paces for improving the coal efficiency of thermal power generation and electricity efficiency

of economic activities as well as coal switching in order to achieve the commitment CO₂ mitigation goal in 2030 were obtained, which provided a clear guideline for future policy makers.

The remainder of this work is constructed as follows: Section 2 introduces the double-layer STIRPAT model developed to explore the long-term relationship among coal switching, energy efficiency improvement in electricity production and consumption and the CO₂ emissions trend in China during 2013–2040; Section 3 introduces the data processing methods; Section 4 develops the scenarios; Section 5 explains the results and provides the policy implications for China; and the final section concludes this work.

2. Methodology

2.1. Description

Scenario simulation A is an effective way for policy makers to preview the effects of a policy that is designed to mitigate CO₂ emission. For several years' development, there are many kinds of scenario analysis methods that can be used to trace the long-term trend of CO₂ emissions, which can be divided into 2 categories: (1) the ones based on econometric modelling [22,31,32]; (2) and the ones based on long-run systematic energy analysis tools, such as LEAP [5,24,33], system dynamic [34] and so on. Obviously, these two kinds of methods are quite different; the econometric scenario models are useful to identify the key factors that influence the trend of CO₂ emissions and also can clearly show the path that each factor's effect exerts in every stage, while the long-run systematic energy analysis tools are more suitable for simulating a CO₂ emissions system with complex internal influences among all parts of the system. However the difficulties in accurately carving out the internal relationships may result in large simulating errors. In this regard, through systematic tests and examination of historical data, the econometric scenario analysis can minimize the simulating errors and thus build more accurate equations that describe the long-term relationship among all the factors selected.

Because of the different inherent theories it is based on, econometric scenario analysis can be normally grouped into two kinds of research in simulating the trends of CO₂ emissions. One is based on the Kuznets curve theory [31,35], and the other one is based on IPAT (Impact of Population, Affluence and Technology) theory. In Kuznets curve theory, it is assumed that CO₂ emissions are mainly caused by affluence, while in IPAT theory, the effects of technologies and population are also included. Moreover, because technologies can be decomposed into different factors, scenario analysis based on IPAT theory is superior to Kuznets curve theory in scaling the effects of various factors in contributing to the development of CO₂ emissions.

The basic philosophy in the IPAT model is that the environment is impacted by the growth of population, income and technologies used for economy, and the formula is [36]

$$I = P \times A \times T \quad (1)$$

where I is defined as environment impacts, such as all kinds of pollutants; P is defined as population; A is defined as affluence, such as GDP capita, real income and others; and T is defined as technologies that influence the growth of environment impacts, such as energy intensity, economic structure and so on. Because it is assumed in the IPAT model that the effects of population, income and technologies are the same on environment impacts, it cannot accurately clarify the real relationships. As a result, Dietz and

Rosa developed the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model [37] to evaluate the different effects of P , A and T on the change in environment impacts, which can be calculated as

$$I = aP^b A^c T^d e \quad (2)$$

where a is the constant of the model, b , c and d are the coefficients, and e is the model residual error term.

Equation (2) can be further transformed into

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (3)$$

Equation (3) shows that the elasticity of P , A and T to I can be represented by b , c and d , which means that every 1% increase in P , A and T can result in $a\%$, $b\%$ and $c\%$ of increase in I respectively. Because the technologies influencing CO₂ emissions can be explained by different factors like energy intensity, fuel mix and industrial structure, the STIRPAT model is widely used to express the relationship among different factors that contribute to change in CO₂ emissions [38–41].

2.2. A double-Layers STIRPAT Model

One of the biggest challenges in using the STIRPAT model to simulate the long-term relationship among population, affluence, technologies and CO₂ emissions is that the coefficients obtained by the econometric model depend greatly on what factors are chosen to reflect the technologies, even for the same regions. For example, in both Meng's [42] and Li's [43] research, the driving factors of China's CO₂ emissions are researched, but because of the different factors selected to reflect the technologies, with Meng [42] selecting CO₂ intensity of GDP and Li [43] selecting energy intensity, the elasticities of both population and affluence are quite different in these two studies. The results of Meng [42] show that a 1% increase in population and affluence will result in a 1.81% and 1.91% increase in CO₂ emissions, respectively, while in Li's [43] research, these two figures are 1.12% and 1.31%. This is quite confusing, and in order to conquer this obstacle in using the STIRPAT model, this work developed a double-layer STIRPAT model, the basic framework of which is illustrated by Figure 3. This framework illustrates the thought that CO₂ emissions in China are basically caused by the activities of the population, affluence and energy consumption technologies. The change in energy consumption technologies can be further reflected by the change of fuel mix, industrial structure and some other unknown factors. Thus, the basic STIRPAT model can be further developed into a double-layer model which is formulated as

$$\ln I = \ln a + b \ln P + c \ln A + d \ln ET + \ln e \quad (4)$$

$$\ln ET = \ln ET_1 + \ln ET_2 + \ln ET_3 + \dots + \ln ET_n \quad (5)$$

where ET represents the level of energy consumption technologies, and ET_1, ET_2, \dots, ET_n represent the factors that influence the level of energy consumption technologies. Equations (4) and (5) show that, from a mathematical view, because there exists an equation that can explain the relationship among I and ET , and at the same time an equation describing the relationship among ET and ET_1, ET_2, \dots, ET_n , substituting ET in Equation (4) into Equation (5) can provide the equation that represents the relationship among I and ET_1, ET_2, \dots, ET_n .

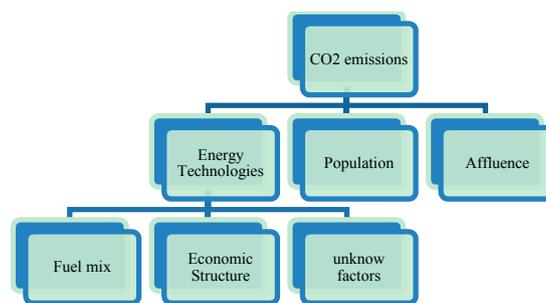


Figure 3. Double-layers STIRPAT Model.

In the above double-layer STIRPAT model, researchers can choose any factor to reflect the change in energy consumption technologies while keeping the coefficients of population and affluence irrelative to the factors chosen. Energy consumption technologies can be evaluated by the energy intensity of GDP, which is well recognized as the most important factor that contributes to CO₂ emissions [44,45]. In China and in this work, because we want to examine the effects of coal switching, energy efficiency improvement of electricity production and consumption on mitigating CO₂ emissions, we chose coal proportion in aggregate energy consumption, electricity intensity of GDP, coal intensity of thermal power generation and tertiary industry proportion in overall economy to regress the change of energy intensity in China.

The final models we used to reflect the long-term relationship among coal switching, energy efficiency improvement of electricity production and consumption can be expressed by

$$\ln I_c = a + b \ln P + c \ln GDP / P + d \ln EI + \ln e \quad (6)$$

$$\ln EI = f + g \ln FM_c + h \ln EI_{elec} + i \ln CI_p + j \ln IS + \ln k \quad (7)$$

where I_c represents the amount of CO₂ emissions, P represents the size of population, GDP/P represents the gross domestic products per capita and is used to reflect people's affluence in China, EI represents the energy intensity of GDP, FM_c represents the coal proportion in aggregate energy consumption, EI_{elec} represents the electricity intensity of GDP and is used to reflect the electricity consumption efficiency, CI_p represents the coal intensity of thermal power generation and is used to reflect the energy efficiency of electricity production, IS represents tertiary industries' share in aggregate GDP, a and f are the model constants, e and k are the residual errors, and b, c, d, g, h, i, j are the coefficients that need to be forecasted.

3. Data Processing and Scenario Development

3.1. Data Collection

The historical period of the data is from 1980 to 2012, and the scenario period is from 2013 to 2040. The data on each kind of fuel consumption and coal intensity of thermal power generation were self-collected from China Energy Statistical Yearbook 1986, 1991, 1996, 1999, 2004–2013 [6–11]; data on amount of CO₂ emissions were estimated by multiplying the CO₂ emission factor [12] and consumption of different kinds of fuels. The data on real GDP were processed by GDP value in 2012 multiplying its growth rate each year, and the energy intensity was calculated by real GDP dividing aggregate energy consumption in equivalent tons of coal, and the data on aggregate energy consumption

were collected from China Statistical Yearbook 2013 [46], the same as the data on population, electricity consumption, proportion of coal in aggregate energy consumption, and share of the tertiary industry in aggregate GDP. The electricity intensity of GDP is calculated by dividing the aggregate electricity consumption by aggregate real GDP.

3.2. Data Processing

3.2.1. Unit Root Tests

In order to find the long-term equilibrium relationships among all the variables that appeared in Equations (6) and (7), it is necessary to test the stationary state of the time series before regressing, which is called a unit root test. Only if the unit root test results indicate that all the time series are stationary, which means the development of the series is independent of time, can the regressing results among the series be considered to be the long-term equilibrium relationship among all the variables. However, in real economy, the time series of most variables are not stationary. For non-stationary series, there is still the possibility of finding long-term equilibrium relationships among them. For this purpose, firstly, the unit root test should be used to find if the 1st differences of non-stationary series are stationary, that is, the series integrated in the same order 1, $I(1)$; if this is true, then the cointegration test should be used to test if these series are cointegrated in the long run, and only if the cointegration test indicates there is at least one cointegrated equation existed among the variables can the regression be done.

Of all the unit root tests, ADF, DF-GLS and PP are the most commonly used methods to test the stationary state of a time series. The unit roots test was done by the EViews 7 software in this work. EViews series software is a commonly used econometrics tool for anyone working with time series, cross-sections, or longitudinal data. By using EViews, researchers can efficiently and easily manage their data, perform econometric and statistical analysis, generate forecasts or model simulations. The unit root test results for each of the variables are shown in Table 1. In that table, it can be seen that, under the DF-GLS and PP test scheme, the first differences of all the series tested as stationary. Although for the ADF test, neither the level of CI nor its first difference tested as stationary, but the DF-GLS and PP test results show that its first difference is stationary. Because each unit root test model has its own shortcomings and advantages for variables with different characteristics, it is difficult to say which one is superior and in our work we judge whether variables are stationary according to the results that most of the methods support, so we can still conclude that the first difference of CI tested as stationary. Thus, the unit root tests of this research show that the first differences of all the variables are stationary, that is, they are integrated of order 1, $I(1)$.

3.2.2. Cointegration

Given that all the variables are integrated of the same order 1, $I(1)$, we need to use the cointegration test to check whether there is a long-run relationship among the variables. The Johansen test is used to test the cointegration of the series in our work. The Johansen test, which is named after Søren Johansen, is a procedure developed to test the cointegration of several $I(1)$ time series. Because our unit root test results indicate that all the series in our work are $I(1)$, the Johansen test is quite suitable for this work. The cointegration test results are shown in Table 2. For the variables $\ln I_c$, $\ln P$, $\ln GDP/P$ and $\ln EI$, the

test results refuted the assumptions that there is no cointegration equation and at most 1 cointegration equation, but agreed with the assumptions that there are at most 2 cointegration equations among them. Thus, it can be inferred that $\ln I_c$, $\ln P$, $\ln GDP/P$ and $\ln EI$ are cointegrated. Similarly, for the variables $\ln EI$, $\ln FM_c$, $\ln EI_{elec}$, $\ln CI_p$, and $\ln IS$, the testing results imply that there is one cointegration equation existing among them, so it can also be concluded that $\ln EI$, $\ln FM_c$, $\ln EI_{elec}$, $\ln CI_p$, and $\ln IS$, are cointegrated.

Table 1. Unit roots tests results.

Variables	ADF		DF-GLS		PP	
	Level	1st Difference	Level	1st Difference	Level	1st Difference
$\ln I_c$	0.081	-2.801 *	0.030	-2.385 **	0.686	-2.835 *
$\ln P$	-2.245	-2.834 *	0.859	-2.665 **	-7.760 ***	-
$\ln GDP/P$	1.495	-3.453 **	0.203	-1.968 **	0.606	-3.362 **
$\ln EI$	-1.039	-3.103 **	0.212	-2.955 ***	-1.335	-1.612 *
$\ln FM_c$	-0.193	-4.404 ***	-1.257	-2.218 **	-0.799	-4.520 ***
$\ln EI_{elec}$	-1.263	-3.598 **	-0.486	-3.203 ***	-2.417	-2.445 **
$\ln CI_p$	4.187	0.570	0.123	-2.563 **	3.959	-3.712 **
$\ln IS$	-2.129	-3.819 ***	-0.015	-3.881 ***	-2.462	-3.753 ***

* Statistical significance at the 10% level; ** Statistical significance at the 5% level; *** Statistical significance at the 1% level.

Table 2. Cointegration tests results.

Group of Variables	Hypothesized No. of CE(s)	T-Statistic	Prob.
$\ln I_c$, $\ln P$, $\ln GDP/P$, $\ln EI$	None *	53.864	0.0123
	At most 1 *	32.183	0.0261
	At most 2	12.788	0.1228
	At most 3 *	4.575	0.0324
$\ln EI$, $\ln FM_c$, $\ln EI_{elec}$, $\ln CI_p$, $\ln IS$	None *	74.990	0.0182
	At most 1	40.066	0.2202
	At most 2	19.188	0.4795
	At most 3	15.495	0.4183
	At most 4	0.047	0.8287

* Statistical significance at the 10% level.

3.2.3. Estimation of the Long-Term Relationship

The unit root tests and the cointegration tests show that there is a long-term equilibrium relationship among the variables that we want to examine in this work, so we need to use some kind of estimators to regress the equations. The FMOLS (Fully Modified Least Squares) regression model was selected as the estimator of long-term relationships among the variables. Although OLS (Ordinary Least Square) estimators of the cointegrated vectors are super-convergent, their distributions are asymptotically biased and also exhibit small sample bias, while the FMOLS technique outperforms OLS in these regards [47]. The estimation was done with EViews 7, and the result for the long-term relationship among $\ln I_c$, $\ln P$, $\ln GDP/P$ and $\ln EI$ was firstly obtained as

$$\ln I_c = 0.548 \ln P + 1.143 \ln GDP / P + 1.212 \ln EI$$

$$\text{Adjusted } R^2 = 0.998, \text{ DW} = 0.563 \quad (8)$$

Although the high value of adjusted R^2 shows that the actual curve is greatly fitted by the estimating curve, the value of DW shows that the residual error series is positively auto-correlated; it is necessary to correct the autocorrelation of residual error series in order to get an accurate estimation of the long-term relationship, so we added the first lag of residual error into the model and the simulation result is

$$\ln I_c = 0.542 \ln P + 1.158 \ln GDP / P + 1.246 \ln EI$$

$$\text{Adjusted } R^2 = 0.999, \text{ DW} = 2.021 \quad (9)$$

Equation (9) shows that after adding the first lag of residual error into the model, the fitting effect was slightly improved and the autocorrelation of residual error series is well eliminated, so Equation (9) can be used to reflect the long term relationship between $\ln I_c$, $\ln P$, $\ln GDP/P$ and $\ln EI$.

Similarly, the equation that used to reflect the long term relationship among $\ln EI$, $\ln FM_c$, $\ln EI_{elec}$, $\ln CI_p$ and $\ln IS$ was obtained after adding both the first and second lag of residual errors and can be expressed as

$$\ln EI = -7.031 + 1.359 \ln FM_c + 1.051 \ln EI_{elec} + 1.549 \ln CI_p - 0.691 \ln IS$$

$$\text{Adjusted } R^2 = 0.995, \text{ DW} = 1.989 \quad (10)$$

By substituting EI into Equation (9) from Equation (10), it can be seen the final equation that describes the long term relationship among $\ln I_c$, $\ln P$, $\ln GDP/P$, $\ln FM_c$, $\ln EI_{elec}$, $\ln CI_p$ and $\ln IS$ should be

$$\ln I_c = -8.758 + 0.542 \ln P + 1.158 \ln GDP / P + 1.7051 \ln FM_c$$

$$+ 1.309 \ln EI_{elec} + 1.9301 \ln CI_p - 0.861 \ln IS \quad (11)$$

4. Scenario Development

4.1. Elasticities

Equation (11) shows that the elasticities of P , GDP/P , FM_c , EI_{elec} , CI_p and IS to CO_2 emissions in China are 0.542, 1.158, 1.705, 1.309, 1.930, -0.861 , which means that among all the factors, increase in population, GDP per capita, coal proportion in aggregate energy consumption, electricity intensity of GDP and coal intensity of thermal power generation will result in positive growth of CO_2 emissions, while the increase in share of tertiary industry in aggregate GDP will reduce CO_2 emissions. The elasticities also show that the growth of CO_2 emissions in China is more sensitive to the growth of GDP per capita, proportion of coal in aggregate energy consumption, electricity intensity of GDP and coal intensity of thermal power generation, in which the role of coal intensity of thermal power generation ranks as the top one, followed by coal proportion in aggregate energy consumption, then the electricity intensity of GDP and finally the GDP per capita. The growth in population will also result in positive growth of CO_2 emissions, but its effect is quite low compared with other factors. The increase in the share of tertiary industry in aggregate GDP implies reduction in CO_2 emissions, but the effect is rather low compared with improving the energy efficiency of electricity production and consumption and also reducing coal's proportion in aggregate energy consumption. Therefore, in order to effectively mitigate CO_2 emissions and reach the carbon reduction commitment for 2030, China should make more efforts

to improve energy efficiency of thermal power generation and electricity consumption as well as encouraging coal switching.

4.2. Features of the Scenarios

Based on the above analysis of elasticities of P , GDP/P , FM_c , E_{elec} , CI_p and IS to CO_2 emissions, five different scenarios were developed to track the CO_2 emissions trend in China in 2013–2040, which can be described as

Current scenario (C): In this scenario, the current energy savings and emissions reduction policy mechanisms will be the same as in previous years and China will not make greater efforts to improve the energy efficiency of electricity production and consumption and switch from coal consumption, so we assumed coal intensity of thermal power generation, electricity intensity of GDP, and the coal proportion in aggregate energy consumption will drop at the same rates as the average level throughout the period of 1980–2012, which were 1.38%, 1.00% and 0.215% annually.

Low-coal scenario (S1): In this scenario, China will not make more efforts to improve the energy efficiency of electricity production and consumption, while in order to reduce overall carbon emissions, more policies will be enacted in order to substitute coal consumption with low carbon fuels, like renewable energies, nuclear power and biomass fuels or natural gas. In light of this, we firstly assumed in this scenario that the coal intensity of thermal power generation and electricity intensity of GDP will drop at the same pace as in the period of 1980–2012, which were 1.38% and 1.00%, while the decreasing rate of coal proportion in aggregate energy consumption will be accelerated to 2 times the historical level, which would be 0.215% during 1980–2012 and thus 0.43% in the future. Meanwhile, we slightly changed the developing trend of coal intensity of thermal power generation, because it was found that the coal efficiency of thermal power generation cannot always be improved substantially. Figure 4 shows the developing trend of coal intensity of thermal power generation for different countries in last few years, and it can be clearly seen that in the earlier years, an outstanding fall could be achieved for most of the countries, but the sharp decrease disappeared when a certain level of improvement was achieved (Japan was about 316, Korea 302 and Italy 275 g coal equivalent (gce)/KWh). According to this finding, we assumed that for China, when the coal intensity of thermal power generation reaches the level of Italy in 2010, about 275 g coal equivalent (gce)/KWh, the annual drop pace will decrease from 1.38% to 0.2%. Because in this scenario, it is assumed coal fuel is highly encouraged to be substituted by other low carbon energies, the coal share in overall primary energy consumption is assumed to drop by 2 times the average pace of the historical period, which will be 0.43% annually.

Coal-efficient thermal power generation scenario (S2): In this scenario, China will make more efforts to enact several policies to encourage or force thermal power generators to improve coal use efficiency and thus reduce the overall CO_2 emissions due to compressed coal combination. At the same time, the efforts put into substituting coal consumption with other low-carbon fuels and the improvement in electricity consumption efficiency will not change. As a result, we assumed that in this scenario, the electricity intensity of GDP and coal proportion in aggregate energy consumption will develop at the same rate as in 1980–2012, which decreased by 1.00% and 0.215% annually, while the coal intensity of thermal power generation will drop by 2 times the historical average level, which was 2.07% per year before the level of 275 gce/KWh achieved, and after that it will decrease by 0.2% every year.

Electricity consumption-efficient scenario (S3): In this scenario, China will mainly resort to improving electricity consumption efficiency in order to achieve the CO₂ mitigation goal, so the reduction rate for coal intensity of thermal power generation and coal proportion in aggregate energy consumption will be the same as in 1980–2012, which was 0.215% and 1.38% annually, while the reduction pace of electricity intensity of GDP will be accelerated to 2 times the historical average level, 2.00% per year.

Integrated scenario (S4): In this scenario, China will make the same efforts to improve the energy efficiency of electricity production and consumption as well as to substitute final coal consumption with low carbon fuels. Consequently, we assumed that the decrease rate of electricity intensity of GDP, coal intensity of thermal power generation and coal proportion in aggregate energy consumption would be the same and all of them would be 1.19%, which was the historical average developing level of both coal intensity of thermal power generation and electricity intensity of GDP. That means for the coal proportion in aggregate energy consumption, the decrease rate will increase at 5.5 times the average pace in 1980–2015, the decrease rate of electricity intensity of GDP will increase slightly and the decrease rate of coal intensity of thermal power generation will slow down slightly. The same treatment was still conducted for coal intensity of thermal power generation when the level of 275 gce/KWh is achieved.

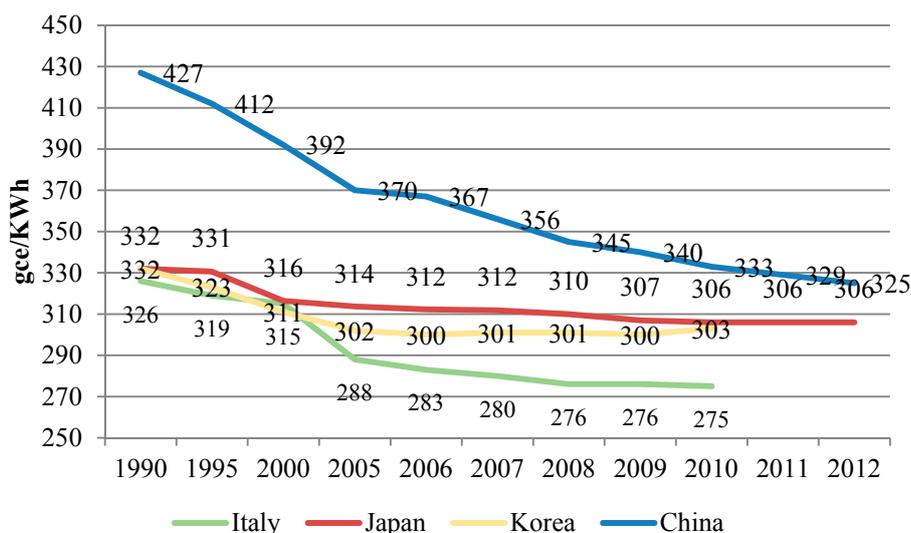


Figure 4. Coal intensity of thermal power generation for several countries.

For all the scenarios, the growth of population and GDP were assumed according to the IEA forecasting results for China [48], and the growth of share of tertiary industry in GDP was assumed based on the forecast by Jiang [49], which can also be seen in Table 3.

Table 3. Assumption for growth of population, GDP per capita and tertiary industrial proportion in GDP.

Variables	Periods		
	2013–2020	2020–2030	2030–2040
P	0.4%	0.329%	0.244%
GDP/P	6.9%	5.3%	3.2%
IS	0.87%	1.21%	1.13%

5. Results Analysis

5.1. Simulation Results Analysis

The main growth rates and values of variables in C, S1, S2, S3 and S4 are shown in Table 4 and the final simulated trends of CO₂ emissions are shown in Figure 5.

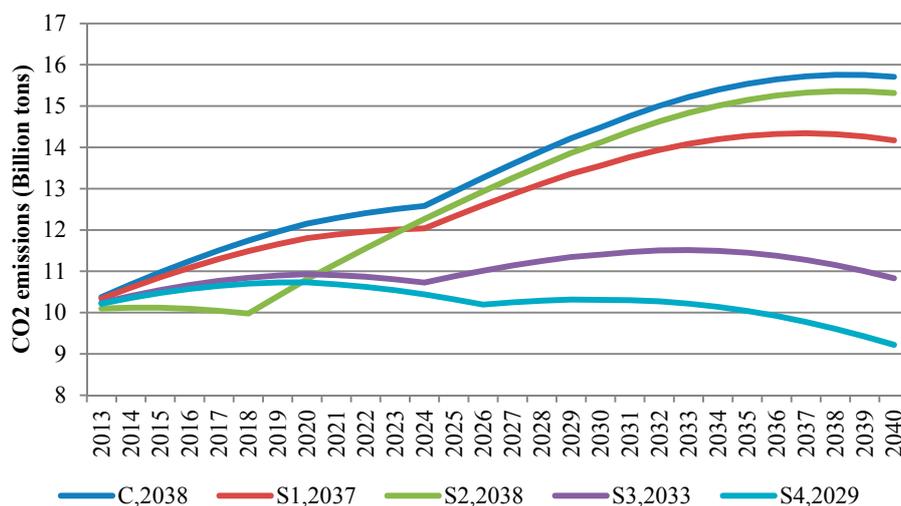


Figure 5. The overall CO₂ emissions in China projected for different scenarios.

Table 4. The results of the main variables in different scenarios.

Scenario	Variables	Growth Rate (%)	Value		
			2020	2030	2040
C	I_c (Billion tons)	1.49	12.152	13.989	14.314
	FM_c (%)	0.215	69.405	67.928	66.480
	EI_{elec} (KWh/Yuan)	1.00	0.088	0.080	0.072
	CI_p (gce/KWh)	1.38	291	272	266
S1	I_c (Billion tons)	1.13	11.799	13.092	12.914
	FM_c (%)	0.43	68.217	65.340	62.584
	EI_{elec} (KWh/Yuan)	1.00	0.088	0.080	0.072
	CI_p (gce/KWh)	1.38	291	272	266
S2	I_c (Billion tons)	1.50	10.806	14.121	15.314
	FM_c (%)	0.215	69.405	67.928	66.480
	EI_{elec} (KWh/Yuan)	1.00	0.088	0.080	0.072
	CI_p (gce/KWh)	2.76	291	274	263
S3	I_c (Billion tons)	0.20	10.926	11.404	10.829
	FM_c (%)	0.215	69.405	67.928	66.480
	EI_{elec} (KWh/Yuan)	2.00	0.082	0.067	0.055
	CI_p (gce/KWh)	1.38	291	272	266
S4	I_c (Billion tons)	-0.37	10.731	10.300	9.218
	FM_c (%)	1.19	64.161	56.922	50.500
	EI_{elec} (KWh/Yuan)	1.19	0.087	0.077	0.069
	CI_p (gce/KWh)	1.19	295	273	267

C: Figure 5 indicates that except S4, the CO₂ emissions of all the other scenarios will increase compared to the level in 2012, and the growth of C is the fastest, which will increase to nearly 16 billion tons in 2040, an increase of 48.27%. The CO₂ emissions peak level of scenario C is 15.753 billion tons, which will be reached in 2038 (Figure 5), and this implies that if China does not change its current carbon mitigation policies, the CO₂ mitigation commitment goal for 2030 cannot be achieved.

S1: As the results of S1 show, the CO₂ emissions will reach over 14 billion tons in S1 by the end of 2040, which is higher than the level in 2012 by 33.76%. The peak CO₂ emissions will be reached in 2037 (Figure 5), a total of about 14.338 billion tons, about 9% lower than the peak level in scenario C. The results of S1 imply that, although encouraging extensive coal switching cannot cause peak CO₂ emissions to come earlier, it is very helpful in reducing the overall amount of CO₂ emissions.

S2: The CO₂ emissions of S2 will reach over 15 billion tons in 2040, an increase of 44.54% comparing with the level in 2012. The peak level will be reached in 2038 (Figure 5), which is the same as in scenario C and later than scenario S1. The peak level is 15.257 billion tons, slightly lower than the peak level in scenario C and much higher than scenario S1.

S3: The fast improvement of electricity intensity of GDP in S3 will help China to achieve the peak CO₂ emissions level of 11.512 billion in 2032, which is much earlier than in scenarios C, S1 and S2, but still cannot meet the commitment requirement. The peak CO₂ emissions level in S3 is 26.92%, 19.71% and 24.55% less than the peak levels in scenarios C, S1 and S2, respectively. The simulation results of S3 show that intensively reducing electricity intensity of GDP can greatly speed up the coming year of peak CO₂ emissions and can also reduce the total amount of CO₂ emissions in China.

S4: The integrated improvements in coal efficiency of thermal power generation and electricity efficiency of economic activities and coal switching in S4 reduce the CO₂ emissions substantially in 2013–2040, a bit more than 9.0 billion tons in 2040, reduced by 41.32%, 34.95%, 39.81% and 14.88% compared with the levels in C, S1, S2 and S3 in 2040, respectively. The peak level of CO₂ emissions in S4 is 10.73 million tons, which is far less than the peak levels in C, S1, S2 and S3. The peak time is 2020, which is much earlier than in scenarios C, S1, S2 and S3. The results in S3 and S4 show that by cooperatively improving the electricity efficiency of economic activities and substituting coal consumption can effectively help China to achieve the CO₂ emissions mitigate commitment.

However, because the peak year 2020 is too much earlier than commitment year 2030, we need to try to modify the decreasing rates of the defined three variables in S4 step by step in order to find a new peak year which is much closer to 2030, since heavy regulation on CO₂ emissions always means a loss of economic growth. We found that after the decreasing rates of all the three variables drop to less than 1% per year, the peak year will suddenly jump from 2023 to 2032, so we kept on trying by slowing down the decrease rates of two of the three variables, and keeping the decrease rate of the other at 1%. As a result, we found four cases with different values of the three variables in which the peak CO₂ emissions years were very close to the committed peak year of 2030 (Table 5). As Table 5 shows, although the peak level years of Case 1, Case 2 and Case 4 were very similar, the peak CO₂ emissions levels were very different. Case 1 performed better than the other 3 cases in regard of reducing carbon emissions, so the decreased rates in Case 1 were chosen as the reference steps in improving the coal efficiency of thermal power generation, electricity efficiency of economic activities and coal switching, which are necessary in order to reach the CO₂ emissions mitigation goal committed to for 2030.

Table 5. Different cases that can meet the commitment peak year requirement.

Cases	Peak CO ₂ Emissions Level (Billion Tons)	Peak Level Year	Growth (%)		
			<i>FM_c</i>	<i>EI_{elec}</i>	<i>CI_p</i>
Case 1	12.96	2029	−0.8	−1	−0.8
Case 2	13.36	2029	−0.7	−0.7	−1
Case 3	13.51	2029	−1	−0.7	−0.7

5.2. Policy Implications

Substituting coal consumption with low-carbon fuels: The results in Case 1 show that China should at least reduce the coal proportion in aggregate energy consumption by 0.8% per year, and this will reduce the coal proportion in aggregate energy consumption by 56.39% in 2040. This reduction pace is much quicker than the historical average level, and that means China should make more efforts in encouraging the consumption of non-coal energies. Actually, China has the potential to increase the share of low-carbon fuels in overall energy consumption. Figure 6 shows the historical development of non-coal fuels' proportion of overall energy consumption in China, it can be clearly seen that the proportions of low-carbon fuels, like nuclear energy and renewable energy, are rather low in China, especially wind, solar and nuclear power. There is a great deal of room for the substitution of renewable energy for coal.

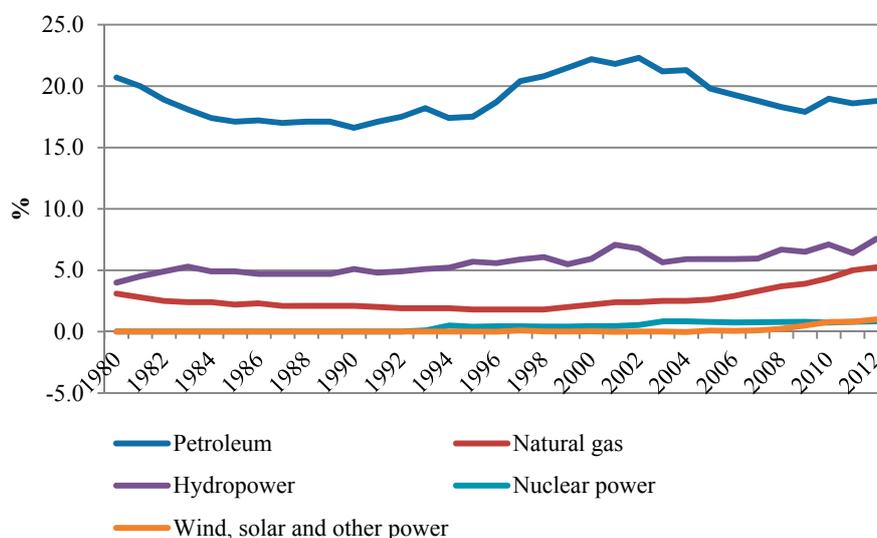


Figure 6. Non-coal proportion in aggregate energy consumption in China from 1980 to 2012.

Improving the coal efficiency of thermal power generation: The results of Case 1 also show that China should keep on improving the coal efficiency of thermal power generation. Although as Figure 4 shows, the coal intensity of thermal power generation was greatly improved in 1990–2012, which decreased by 23.89% at the end of 2012, the level was still much higher than other developed regions. The coal intensity of China's thermal power generation was 325 gce/KWh in 2012, nearly the same level as Japan in 1995, Korea in 1995, and Italy in 1990 [6–11]. Therefore, China should keep on improving the coal

efficiency of thermal power generation; however, given that the pace of coal switching will be accelerated greatly, the pace can be slowed down. This gives the policy makers more opportunity.

Improving electricity efficiency of economic activities: The results of Case 1 show that the electricity efficiency of economic activities should at least keep the same improvement pace as the historical level so as to achieve the commitment CO₂ emissions mitigation goal in 2030. Although China's electricity efficiency of economic activities greatly improved in 1980–2012, decreasing from 0.121 KWh/Yuan in 1980 to 0.095 KWh/Yuan 2012, by 20.74%, when compared with the world average level, or the OECD countries' average level or even the non-OECD countries' average level, the level of China's electricity intensity of GDP is much higher than other countries (Figure 7). This means the electricity efficiency of China's economic activities is very low, so the government should exert even more efforts to encourage improvements in electricity consumption efficiency.

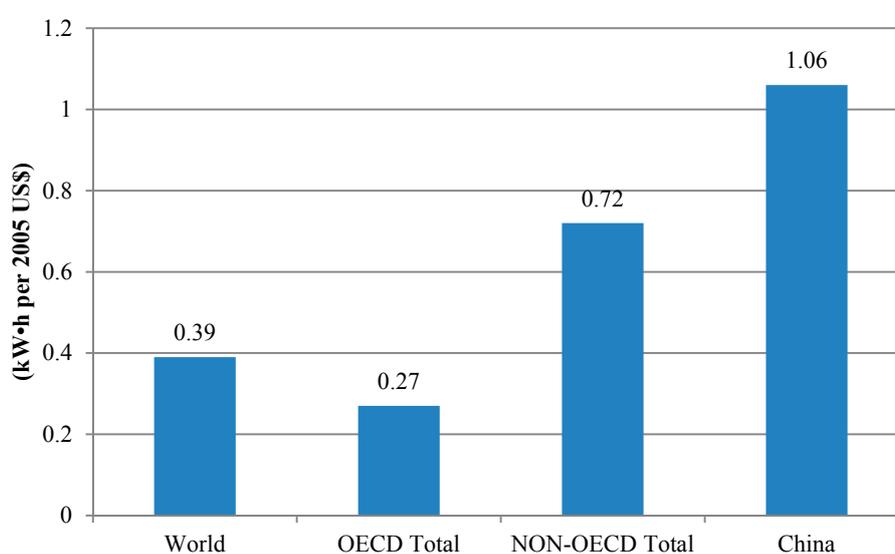


Figure 7. World electricity intensity of GDP in 2011 [11].

6. Conclusions

As the largest CO₂ emissions producer in the world, China has the responsibility to mitigate CO₂ emissions to slow down global warming. This work deals with the problem of what China can do to achieve the CO₂ emissions mitigation commitment by 2030, and the research results indicate that the change in China's CO₂ emissions greatly depends on how much coal accounts for overall energy consumption, how efficient the coal used for thermal power generation is, and how efficiently electricity is used for economic activities. Therefore, in the future, China should at least do the following three kinds of works in order to achieve the CO₂ emissions mitigation goal in 2030: intensively substitute coal fuels with low-carbon fuels, like renewable energy, nuclear power, biomass fuels or natural gas; continue improving the coal efficiency of thermal power generation at a slower pace; and increase the electricity efficiency of economic activities as usual.

Although these findings are quite useful for policy makers to make decisions, there are still some points missing in this work and we continue researching them in the future. The policy implications cannot provide more instructive suggestions for the government to specifically regulate the development

of nuclear energy and renewable energy. Since, in our STIRPAT model, the regression results show that there are no econometrical long-term relationships between the shares of nuclear energy or renewable energy in overall energy consumption and CO₂ emissions, which may be due to their very small size, we cannot simulate their future effects on CO₂ emissions in our model. Consequently, if we want to precisely identify the effects of developing nuclear energy and renewable energy in contributing to CO₂ emissions mitigation, we need to use other research methods to achieve greater insight; these are the main research areas for our future work. Furthermore, for the coal intensity of thermal power generation, in this work we only wanted to examine its overall and long-term performance on the environmental side, so we did not add too much technical analysis, which is another main research point in our future work.

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Author Contributions

Li Li mainly constructed the work, designed the scenarios and analyzed the results; Jianjun Wang was mainly responsible for the model construction and calculation.

Conflicts of Interest

The authors declare no conflict of interest.

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