Journal of Cleaner Production 251 (2020) 119626

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

China's income gap and inequality under clean energy transformation: A CGE model assessment

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ARTICLE INFO

Article history:
Received 27 June 2019
Received in revised form
29 November 2019
Accepted 8 December 2019
Available online 9 December 2019

Handling Editor: Yutao Wang

Keywords:
Computable general equilibrium (CGE) model
NDC targets
Labor market
Income gap

ABSTRACT

To achieve nationally determined contribution (NDC) targets, China has developed a series of low carbon development plans. Among them, the clean energy transformation is very crucial. This study evaluates the impact of a set of policies including the development of renewable energy, upgrading heavy industry, and energy efficiency improvement on China's income gap between 2012 and 2050. A dynamic computable general equilibrium (CGE) model with detailed representations of economic activity, an upgraded labor market and disaggregated labor types based on statistical and survey data is used. Our research provides support for the necessity of low-carbon policies to achieve NDC targets. Results show some key findings. First, low-carbon policies have the greatest impact on employment across all energy industries, with negative impacts in most traditional energy sectors and positive impacts in most renewable power sectors. Second, labor will continue to migrate from rural to urban areas with the transformation of the economic structure and the urbanization rate will further increase, reaching a maximum of around 70%. The reduction of the rural population will bring new opportunities for the modernization of agriculture, increasing the income of rural residents and realizing the equitable development between urban and rural areas. Third, the income gap among urban residents will widen due to the different level of labor demand for employees with different education levels.

1. Introduction

The gap between rich and poor is an issue that is increasingly prominent in today's society. According to OECD research, economic inequality is getting worse. In the 1980s, the richest 10% of the population in OECD countries earned seven times more than the poorest 10%. They now earn nearly ten times more in 2012 (Brian, 2015). More seriously, the inequality of environmental impacts or policies on different people will further exacerbate economic inequality. Some studies have analyzed income inequality that is related to climate change and low carbon development. As global temperatures continue to increase, the challenges of adaptation and mitigation of climate change tend to increase, and economic inequities will further expand, according to the Stern Report (Zenghelis, 2006). (Boyd et al., 2007) have pointed out that adopting clean development mechanisms (CDM) for low-income communities would improve social equity (Mingwen et al., 2009). constructed an econometric model and found that carbon taxation had expanded the income distribution gap between capital owners and labor owners (Huang et al., 2019). simulated the impact of carbon market and revenue distribution policies on different household groups in China using the CGE model. However, most studies have focused on specific mitigation projects or specific resident groups, and some studies generally focus on quantifying income changes that occur due to transfer payments between government and residents (Saelim, 2019; Tran et al., 2019). Few studies have explored the impact of low-carbon policies on the income of all household types from a labor market perspective.

In response to the climate change challenge, many countries ratified the Paris Agreement, and the Nationally Determined Contribution (NDC), as submitted to the United Nations Framework Convention on Climate Change (UNFCCC), explores low-carbon development pathways. China, which currently has the world's highest level of carbon dioxide emissions, has attracted the

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https://doi.org/10.1016/j.jclepro.2019.119626
0959-6526/

attention of many researchers (Wang and Yang, 2018; Zhang, G. et al., 2018; Zhang, T. et al., 2018). (Liu et al., 2013) proposed that China must move away from coal and boost recycling and renewable energies (Chen et al., 2016). and (Tao et al., 2011) predicted that China would adjust its the energy structure under different low-carbon scenarios through top-down models, concluding that China's renewable energy industry including hydro, wind and solar will develop rapidly in the future. Industrial structures also play an important role in carbon emissions (Zhang et al., 2014). (Chang, 2015) identified key economic sectors and an optimized production structure with respect to CO2 emissions (Zhou et al., 2013). noted that an industrial structural adjustment was an important component of the development of a low-carbon economy. The literature shows clearly that, for China to achieve its NDC targets, low carbon policies must be introduced to change the energy and industrial structure (Jiankun et al., 2011; Wang et al., 2019; Wei et al., 2017). The flow of labor resources among various economic sectors is an issue that requires further study.

Employment is a key indicator for assessing low-carbon development, and it is closely related to household income and social stability. Some scholars use a bottom-up approach to calculate the amount of employment generated by low-carbon technologies. For example (Llera et al., 2013), developed an analytical model to forecast employment in the Spanish polyvinyl (PV) industry, and the results showed that the installation of a 2 MW power plant would employ 60 people per-year (Sooriyaarachchi et al., 2015). discussed the job potential created throughout the value chain of renewable energy technologies and found that the renewable energy industry and its corresponding value chains were creating jobs globally (Thornley et al., 2008). focused on the potential job creation in rural economies of bioenergy systems, and they found that such enterprises could create 1.27 person years of employment per GWh of electricity produced. The bottom-up methods achieve better transparency in terms of the model structure. However, when we consider the linkages among sectors, the top-down models, especially CGE models, provide one of the most complete views of an economy since CGE models incorporate all economic agents (households, firms, government, foreign sector) in an integrated way that is compatible with microeconomic theory and data, and are becoming more popular. At present, a large number of researchers have carried out many environmental economics studies using the CGE model (Hu et al., 2018; Ji, 2005; Liu et al., 2017; Sun and Kuang, 2015). Some scholars have also considered the relationships among different industries and analyzed the impact of low-carbon policies on employment through top-down methods, such as Input-Output (IO) analysis and CGE models (Mu et al., 2018). quantified the full scope of job changes (direct, indirect and induced) brought about by renewable energy development in China. This study used a CGE model of China, and the results showed that for every 1 TWh expansion of solar PV and wind power, up to 45.1 thousand and 15.8 thousand, respectively, direct and indirect jobs in China could be created (Siriwardana et al., 2011). built a CGE model to analyze the impact of a carbon tax on the Australian economy and found that sectors that lost employment were subject to a higher burden of carbon taxes due to their high emission intensity (Perrier and Quirion, 2018). indicated that positive employment impacts can be achieved by shifting investment toward labor-intensive or low-paid sectors, according to IO and CGE models. (Wu et al., 2016), using a CGE model, forecast that total employment in Shanghai would decrease by 42,406 people by 2030 because of an emissions trading system scenario. In such top-down studies for both China (Dong et al., 2014; Yong-sheng, 2010) and other countries (Çetin and Eğrican, 2011; Markandya et al., 2016; Perrier and Quirion, 2018), researchers consistently hold the conclusion that labor will flow from traditional energy-intensive industries to new energy industries as a result of low-carbon development.

There is a difference in the proportion of labor types (including gender, region and level of education) in different sectors. Thus, labor mobility among sectors will have an impact on the labor market due to the demand for different types of labor changes. For instance, since the majority of rural migrant workers in China are uneducated and do not have special skills, they can only complete for less technical or non-technical jobs like construction and service (restaurants and food-related businesses) (Keung Wong et al., 2007; Wu et al., 2008). Some studies have also identified the differential choices made in the labor market by workers as well as labor market discrimination and employment segregation (Blau, 2016; England, 2017). (Bresnahan et al., 2002) concluded through empirical analysis at the enterprise level that some innovative companies tended to use more skilled labor. In addition, changes in labor demand will further drive labor migration from rural to urban areas. Studies have shown that, in the future, China's urbanization rate would reach around 70% by 2050 (Gu et al., 2017; Shen et al., 2005), which is much higher than the current level. Changes in the supply and demand of the labor market will affect the wage levels of differently employed people, which will ultimately affect household income.

In light of these considerations, this study evaluates the impact of low carbon policies on different industries in China and identifies its impact on the labor market from the characteristics of labor types among sectors. The changes in the income levels of different groups, along with social justice issues, are discussed by means of analyzing the connection between wages and household income that is involved in China achieving its NDC targets. To identify these effects, we built a dynamic CGE model of China with disaggregated labor types and re-constructed the urban and rural employment markets. This study addresses certain gaps in the literature. First, our research suggests the government has important opportunities and challenges in terms of the employment market, and different types of labor face different situations presented by the development of low-carbon industries; the considerations have been neglected in most relevant studies. Second, to quantify the employment and economic impact, we establish a comprehensive CGE method with disaggregated labor sectors based on statistical data from China's national demographic census and survey data gleaned from independent demographic research, which can support more relevant research. Third, our study discusses the income changes of different groups that will occur as China works to achieve its NDC targets; our study investigates specifically the labor market based on a complete economic system, which is a novel topic and has important policy implications.

2. Methodology

This study develops a dynamic CGE model of the Chinese economy which is calibrated to the 2012 Input-Output table of China (NBS, 2016) and the 2012 energy balance table (NBS, 2013a) with 42 aggregated production sectors (Appendix A). The model has been used for some economic and environmental issues (Huang et al., 2019; Mu et al., 2018). Based on the CGE model, the labor market is divided into rural and urban markets to take China's urbanization into consideration. The labor sector is disaggregated into 28 categories by education level, gender and region in order to better analyze the impact of low-carbon policies on different labor types. In addition, the model links different types of labor and household sectors to analyze changes in income due to changes in the labor market.

2.1. Basic model structure

Our model structure is shown in Fig. 1. The basic model includes producers and representative consumers, as well as commodity and factor markets. Producers invest in production factors and intermediate inputs, provide goods and services to other producers and representative consumers, and determine the output of goods and services and the optimal input combination under the constraints of production technology according to the principle of cost minimization. Representative consumers earn income through the supply of taxes and factors of production, and, based on the principle of utility optimization, such consumers determine the overall consumption of goods and services and the optimal combination of consumption under budgetary constraints. Price adjustment drives the market for all commodities and factors toward the equilibrium state of supply equaling demand; i.e., the general equilibrium state of the overall economic system.

In the production block, multi-level nested functions are adopted to describe the inputs and outputs that are generated during production activities. The Leontief function is built in the first level of the nested structure to synthesize KEL (capital-energy-labor) bundles and non-energy intermediate demand bundles into sectoral output at a fixed ratio, as shown in Eq. B.1-Eq. B.4 in Appendix B. In the second level, energy, capital and labor are aggregated by the constant elasticity of the substitution (CES) function, as is typical of CGE models, to simulate the different substitution possibilities across factors in each sector. Our research first couples energy and capital into added value and then couples this result with labor; the method has been widely used in CGE models. At the third level, the AL bundle is split into labor demand by skill, while the KE bundle is split into energy and capital. At the fourth level, energy demand by fuel type is combined to generate energy output. Eq. B.5-Eq. B.8 in Appendix B show the second level production functions, and the functions of the other levels are similar. The alternative elastic values in the production and utility functions are mostly derived from some classic CGE model studies (Chen et al., 2015; Wing, 2006).

In the consumption block, we include two representative consumers: government and households. The government receives revenues from a variety of tax instruments (income, indirect trade, and factor taxes), net of subsidies and transfers. Government income is allocated to goods and services and the aggregate expenditures are fixed in real terms. Household income comes from labor wages, investment income, and transfer payments, and this income is allocated to goods and savings at an exogenous rate that is calibrated to the social accounting matrix. Each representative household is assumed to maximize utility by consuming different goods and services as modeled by the Linear Expenditure System (LES) specification.

Similar to other CGE models, the CGE model that we use in our study adopts the Armington hypothesis (Armington, 1969) in the international trade block, which means there is not complete replacement between domestic production and imported production, but there is a certain amount of substitution. The Armington hypothesis is consist with the phenomenon that most sectors include both imports and exports. The model we use assumes that there is an Amington department that is responsible for the distribution of goods in the domestic market. Production, consumption and investment activities do not consume domestically produced goods, but rather Amington goods, which are aggregated according to domestically produced and imported goods. The production of Armington products is also calculated using the CES production function. In terms of exports, domestically produced goods are considered to be the supply to the domestic market in addition to exports, as shown in Fig. 2. The distribution of domestically produced commodities is represented by the Constant-Elasticity-of-Transformation (CET) function.

Finally, in the commodity market and the factor market, the equilibrium price makes the optimal supply and demand equal, and the economic system reaches a stable equilibrium. In the dynamic mechanism, the model considers four driving factors: labor growth, capital accumulation, supply changes of natural resources, and

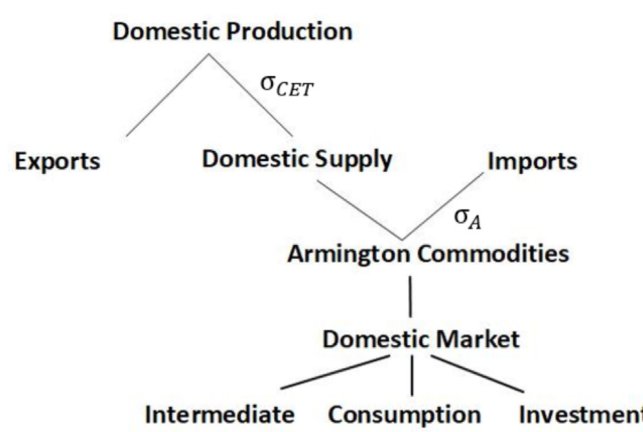

Fig. 2. Armington structure.

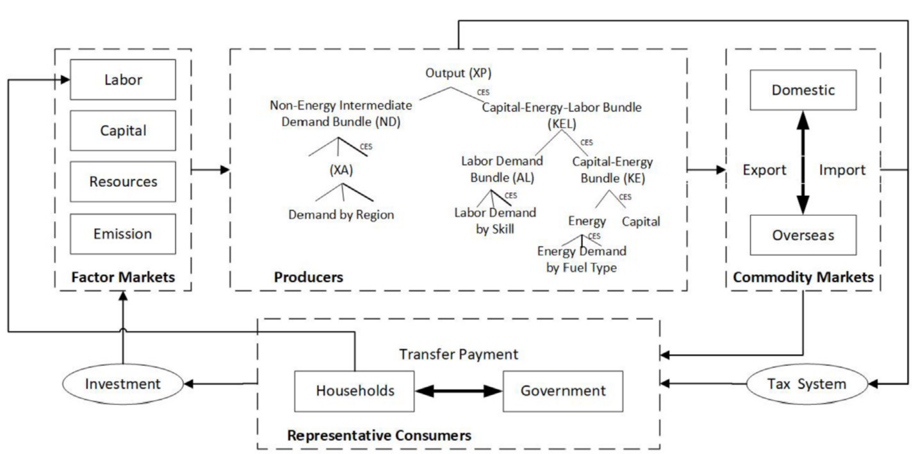

Fig. 1. Model structure.

improvement of production technologies. The equilibrium solutions for each period are obtained by recursive dynamic mechanisms, as agents are assumed to be myopic and to base their decisions on static expectations about prices and quantities.

2.2. Labor disaggregation and market

Although labor is an important production factor in the CGE model, most CGE models have adopted idealized assumptions for the labor market; that is, they assume that the labor supply is fixed and the wage level can be fully adjusted to balance supply and demand in the labor market. This simplification does not suffice to explain the changes in the labor supply that accompany urbanization process or differences in wage levels among industries; this limitation results in significant deviations between the model simulation results and the actual situation. In this study, we modify the labor block in the CGE model to include the labor type disaggregation and the improvement of labor market mechanisms.

Theoretically, labor compensation is the product of average wages and number of workers for a specific sector and labor type. The 2010 China Population Census data (NBS, 2011b) includes the total employment in various industries, as well as the employment of different types of labor. The principles of the division of labor type include gender (male or female), urban and rural location, and level of education (uneducated, primary, junior high school, high school, college, undergraduate or postgraduate). On this basis, our research uses the ratio of total employment in China in 2012 and 2010 according to data from the statistical yearbook (NBS, 2011a, 2013b) to adjust the census data and obtain the employment quantity of disaggregated labor types in various sectors in 2012. The China Household Income Survey (CHIP) data, produced by the China Income Distribution Institute of Beijing Normal University (CIID, 2013), is used to estimate the average wage level of China's disaggregated labor types. CHIP was published in 2013 with a total sample size of 26,527. The survey data includes the sample's wage level, gender, urban and rural sources, and education level, which is consistent with the census data regarding the labor type. According to the CHIP data, the average wage level of China's disaggregated labor types can be estimated, as shown in Appendix C. Based on the above data, and according to Eq. (2.1), the disaggregated labor compensation is calculated and transferred to different household sectors; more details can be found in (Huang et al., 2019). In the China Statistical Yearbook 2012, urban and rural residents were divided into five groups, respectively, according to income level, and household proportions were obtained from the National Bureau of Statistics, as shown in Appendix D. In addition, according to the CHIP database, the composition of the labor type of each household group is counted, and our input-output table is expanded. After this initial allocation, the minimized weighted entropy distance method is used to balance the disaggregated SAM table.

$$LV_{l,i} = \frac{LAW_l}{\sum_l \sum_i (LAW_l \times LQ_{l,i} / \sum_l \sum_i LQ_{l,i})} \times \frac{LAV_i}{\sum_i LQ_{l,i}} \times LQ_{l,i} \tag{2.1}$$

where.

$LV_{l,i}$ = labor compensation of type l in sector i
LAW_l = average wage for labor type l
LAV_i = total value of labor compensation in sector i
$LQ_{l,i}$ = employment quantity for labor type l in sector i

In the labor market, with reference to (Mu et al., 2018)'s work, we introduce a wage curve function in the CGE model, which is used to describe the relationship between unemployment and real wages. The adjustment of the wage level is determined by the model endogenously, so that labor demand is equal to labor supply after deducting unemployment. After that, the CET function is used in the model to reflect the distribution of labor among different industries. This treatment reflects the cross-sectoral transfer of labor, and it also demonstrates that the wage levels of different industries in the equilibrium state are different, as shown in Eq. (2.2). In addition, the labor market equilibrium condition is upgraded using this method, which balances labor supply and demand in rural areas and urban areas separately to better simulate the changes in regional labor supply that will be caused in the future by China's continued urbanization.

$$TLS_r = \left(\sum_i \alpha_i^{LCET} \times LS_{i,r}^{\frac{\sigma^{LCET}-1}{\sigma^{LCET}}} \right)^{\frac{\sigma^{LCET}}{1-\sigma^{LCET}}} \tag{2.2}$$

where.

TLS_r = total labor supply in region r
$LS_{i,r}$ = labor supply in sector i in region r
α_i^{LCET} = share parameter in sector i
σ^{LCET} = elasticity substitution coefficient between sectors

3. Scenarios

We focus on the two low-carbon policies: transformation of the power industry and the carbon market. Structure reforms of the power sector have played a key role in the transformation toward cleaner energy and the achievement of NDC goals in China. To simulate the future development of different power generation technologies in China, especially the development of renewable energy technologies such as wind power and solar power generation, our research disaggregates the power industry according to technology categories, including coal power, gas power, oil power, nuclear, hydro power, wind power, solar power and biomass power. This method is similar to the approach to labor disaggregation (Eq. (3.1)), and the data used is derived from the IEA Energy Database (NEA/IEA/OECD, 2015) and previous studies (Cai et al., 2011; Peters, 2016; Peters and Hertel, 2016a, b). In the dynamic model, the share parameters are setting exogenously to simulate the proportion of different power generation technologies in the future. Further details about this method are provided in the data and scenarios section of this paper.

$$GEN = \left(\sum_t \alpha_t^{TEC} \times TEC_t^{\frac{\sigma^{TEC}-1}{\sigma^{TEC}}} \right)^{\frac{\sigma^{TEC}}{1-\sigma^{TEC}}} \tag{3.1}$$

where.

GEN = total electricity output
TEC_t = output of power technology t
α_t^{TEC} = share parameter of power technology t
σ^{TEC} = elasticity substitution coefficient between technologies

In addition, the carbon market is also simulated in the model. A country's CO2 emissions come from the production sectors and the consumers. The model first calculates the carbon emissions generated by different industries and consumers by multiplying the carbon emission parameters (Eq. (3.2)) (NBS, 2013a). In the production block, a carbon cost variable is added to the production function to simulate the increased costs incurred by the purchase of carbon credits; such costs are determined by the total carbon emissions constraint and the market equilibrium (Eq. (3.3)). In the market closure factor, the carbon revenue is transferred to the government.

$$\mathbf{EFT} = \sum_i \sum_e emit_e \times xap_{i,e} \times (1 - feedstock_{i,e}) \tag{3.2}$$

$$\mathbf{CR} = \sum_i \sum_e \mu \times emit_e \times xap_{i,e} \tag{3.3}$$

where.

$\mathbf{EFT}$ = total emission
$emit_e$ = carbon emission parameters of energy resource e
$xap_{i,e}$ = input of energy resource e in sector i
$feedstock_{i,e}$ = proportion of energy input that is not used as fuel
$\mathbf{CR}$ = carbon revenue
μ = shadow carbon price

The Shared Socioeconomic Pathways (SSPs), as one of the most important scenario frameworks for climate change research, was initially proposed by (Moss et al., 2010) and (Kriegler et al., 2014) but the quantified version was published seven years later by (O'Neill et al., 2017). It includes five SSPs that cover the broad spectrum of future challenges to mitigation and adaptation and translate this into consistent narratives of future developments that are quantified for diverse fields like demography, economic growth and convergence, energy, land-use, air pollution, policies, and trade (Bauer et al., 2017; Popp et al., 2017). In addition, many research institutions have offered predictions and roadmaps of China's green future and low-carbon development, such as *Reinventing Fire China: A Roadmap For China's Revolution In Energy Consumption and Production To (2050)* (Price et al., 2016), produced jointly by China's Energy Research Institute, the Lawrence Berkeley National Laboratory, the Rocky Mountain Institute, and Energy Foundation China; this work was published in September 2016. This report provided an innovative energy roadmap to 2050 using a bottom-up technology model in which China meets its energy needs and improves its energy security and environmental quality. The main policies in achieving NDC targets include the following three points: first, the proportion of fossil energy declines over time while renewable energy increases (Eq. (3.4)), more detail can be found in Appendix E. Second, the share of primary coal use for heavy industry sectors (chemical, non-metallic mineral products, metal smelting and refining) gradually decreases, while the share of primary gas use increases (Eq. (3.5)). Third, autonomous energy efficiency improvements are set based on the findings of the bottom-up technology (Eq. (3.6)).

$$TC_{i,t} = TC_{i0} \times (1 + cgr_{i,t}) \tag{3.4}$$

$$ensh_{i,t} = ensh_{i0} \times (1 + egr_{i,t}) \tag{3.5}$$

$$\lambda_i = \lambda_{i0} \times (1 + AEEI_i) \tag{3.6}$$

where.

$TC_{i,t}$ = total capital input for sector i in year t
$cgr_{i,t}$ = capital input growth rate for sector i in year t
$ensh_{i,t}$ = primary energy use target shares for sector i
$egr_{i,t}$ = primary energy use target shares growth rate

λ_i = energy productivity.

$AEEI_i$ = autonomous energy efficiency improvement

Our research adopts the economic and social forecast data derived from the IIASA SSP database (Riahi et al., 2017), along with details about the low carbon policies reported in the *Reinventing Fire China* report, when building future scenarios. In the Traditional Energy (TE) scenario, low carbon policies are not considered, which means that China's future energy structure will remain similar to the current situation. Fossils remain the main source of energy, and society faces high challenges for mitigation and adaptation to low carbon energy schemes. In the Low Carbon Development (LCD) scenario, China adopts moderate low carbon policies, including increasing the proportion of renewable energy used in the power sector and decreasing the share of primary coal use in heavy industry sectors (chemistry, non-metallic mineral products, metal smelting and refining) to meet the NDC targets. The scenarios and their descriptions are listed in Table 1.

4. Results

4.1. GDP and CO2 emissions

In the LCD scenario, investment in clean energy increased significantly, which will drive the rapid development of GDP while expanding the proportion of renewable energy. By 2050, the GDP under the LCD scenario is 8.75% higher than the TE scenario (Fig. 3). Renewable energy such as solar and wind is estimated to develop rapidly. By 2050, their output levels are 110 times and 3.27 times that of the TE scenario, respectively. The output of traditional energy such as coal is declining. By 2050, the output of the coal industry is only 40% of the TE scenario.

In the TE scenario, China's energy structure does not improve significantly as compared with the current situation, and economic growth still consumes tremendous amounts of traditional energy resources, such as coal. Although energy efficiency has improved, annual carbon emissions continue to grow at a high rate. By 2035, national carbon emissions will reach 30.76 billion tons, which is 3.4 times that of 2012 (Fig. 4). This unsustainable development poses enormous challenges to the mitigation of carbon emissions and adaptation of the economy to low carbon solutions. While carbon emissions should decline after 2035 as economic growth slows, the country's carbon emissions remain at 23.98 billion tons in 2050. In the LCD scenario, China's power industry and certain heavy energy industries will be transformed and upgraded, and the proportion of renewable energy will increase significantly, reducing the role of coal in the country's economic development. In this scenario, China will achieve carbon emission peaks in 2025, which is similar to the optimistic predictions of other studies. With the development of wind power and solar power, carbon emission levels will continue to decline. In the LCD scenario, China's carbon emissions will be 9.09 billion tons by 2050, which basically returns emissions to the 2012 level.

4.2. Labor demand among sectors

Due to low carbon policies, differences in levels of production will lead to differences in labor demand among sectors. This study compared the labor demand across sectors of each of the scenarios outlined above. Compared with the TE scenario, the reduction in labor demand by 2050 in the LCD scenario is concentrated in the traditional energy production sector and high energy consumption sectors, including coal mining products (92.96%), petroleum (52.37%), wood products (14.51%) and coal power (12.96%) by 2050 in LCD scenario. In addition, the labor demand in the hydropower industry will also decrease significantly (13.51%) in this scenario (Fig. 5). The increase in labor demand is concentrated in the new renewable energy and natural gas-related industries. The five

Table 1
Scenarios and descriptions.

Scenarios	Description
Traditional Energy Scenario (TE)	Social and economic data from SSP database; No policy restrictions.
Low Carbon Development Scenario (LCD)	Social and economic data from SSP database; Power structure adjustment, increasing the proportion of renewable energy; Reducing coal input in heavily polluting industries; Improving energy efficiency.

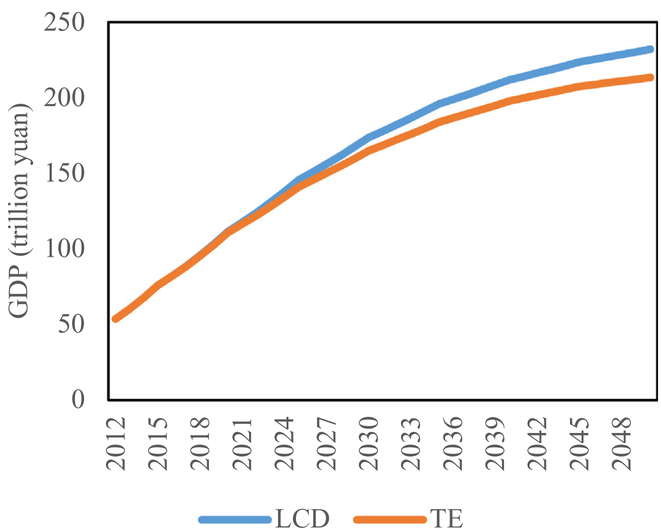

Fig. 3. GDP trajectory.

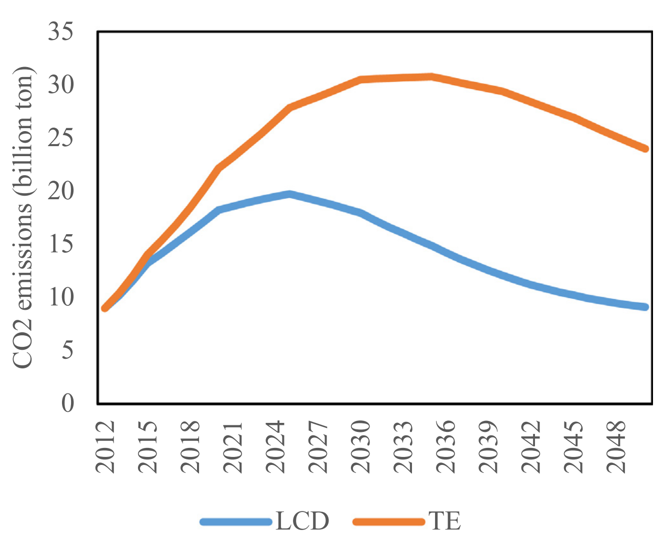

Fig. 4. CO2 emissions trajectory.

sectors with the largest growth rate are solar power (11,315.49%), wind power (211.60%), natural gas power (103.71%), nuclear power (94.21%) and gas production and supply (86.68%) (Fig. 6).

This result shows that, first of all, under the impetus of low-carbon policies, the migration of labor among industries mainly occurs in energy-related industries, but this mitigation has little effect on other manufacturing industries and service industries. Second, under the green development goals, the development of traditional energy industries and high-energy-consumption industries will be restricted, and the proportion of resource-intensive industries in the economic structure will decline. Third, the ratio of fossil and renewable energy sources would change greatly. In terms of traditional energy, natural gas will gradually become a major component of fossil energy usage, because it is cleaner than coal and oil. In terms of renewable energy, the rapid development of new power generation technologies such as solar and wind power will replace traditional renewable energy generation technologies such as hydropower, and the power structure will be further upgraded.

4.3. Impact on labor market

Labor mobility will have an impact on the labor market because of differences in the employment structure. Considering two typical sectors as an example - the coal versus the solar and wind power sectors, the results show that the highest proportion of employed people in the coal sector comprises male urban middle school (30%) and high school (16%) graduates and male rural middle school graduates (20%). However, the highest proportion of employed people in the solar and wind power sectors comprises male urban middle school (15%), high school (22%), junior college (16%) and regular college (11%) graduates (Fig. 7). Differences in the employment categories of the traditional and renewable energy sectors will lead to different opportunities and challenges for different groups of people in China's low carbon development. Taking the labor demand results in the LCD scenario as an example (Table 2), we find that the total employment demand in the coal sector will be reduced by 3573.9 thousand people, of which the employment demand of the male urban middle school (LabMUMS), male urban high school (LabMUHS) and male rural middle school (LabMRMS) will be reduced by 1078.6 thousand people, 710 thousand people and 558.8 thousand people, respectively. The total employment demand for the solar and wind power sectors will increase by 295.8 thousand and 146 thousand, respectively. These two industries will provide 98.1 thousand jobs for the male urban high school (LabMUHS) group, 72.8 thousand jobs for the male urban junior college (LabMUJC) group, 65.5 thousand jobs for the male urban middle school (LabMUMS) group and 48.8 jobs for the male urban regular college (LabMURC) group based on explanation from the known labor type portfolio of the sectors.

First, in the LCD scenario, urban jobs in the labor market will increase, which will attract labor migration from rural to urban areas. China's urbanization rate will further increase. In the two scenarios, the number of people engaged in agriculture will increase slightly due to the increase in population. However, more and more rural people will leave the agricultural sector and choose to work in cities with the increase in the urbanization rate. In the LCD scenario, the employment in agriculture will decrease to only 320 million by 2050, which is 76.9% of the number projected by the TE scenario. Employment in urban regions will increase to 500 million by 2050, 8.46% higher than in the TE scenario (Fig. 8). It can be concluded that in the future, the trend of China's labor migration from rural to urban areas will not change compared with recent years, and with the implementation of low-carbon policies, many

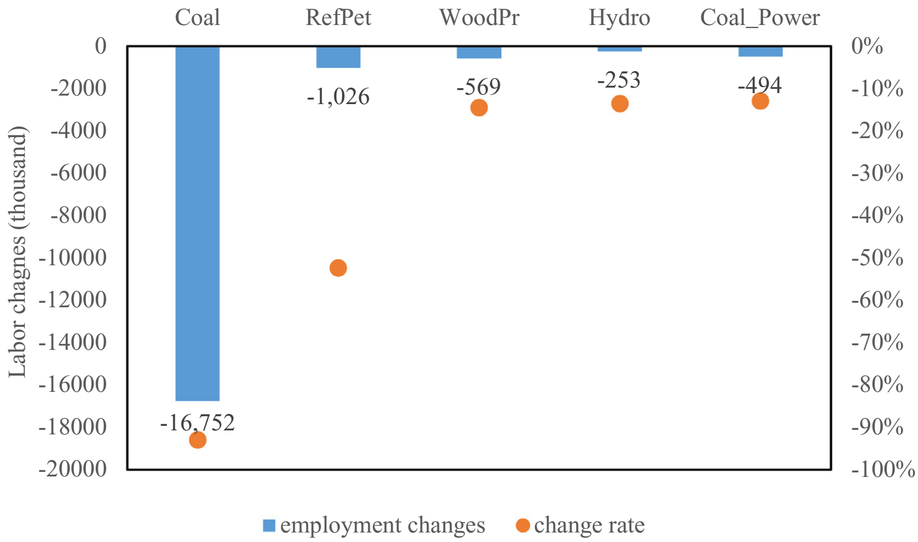

Fig. 5. Labor demand decrease in LCD scenario compared with TE scenario.

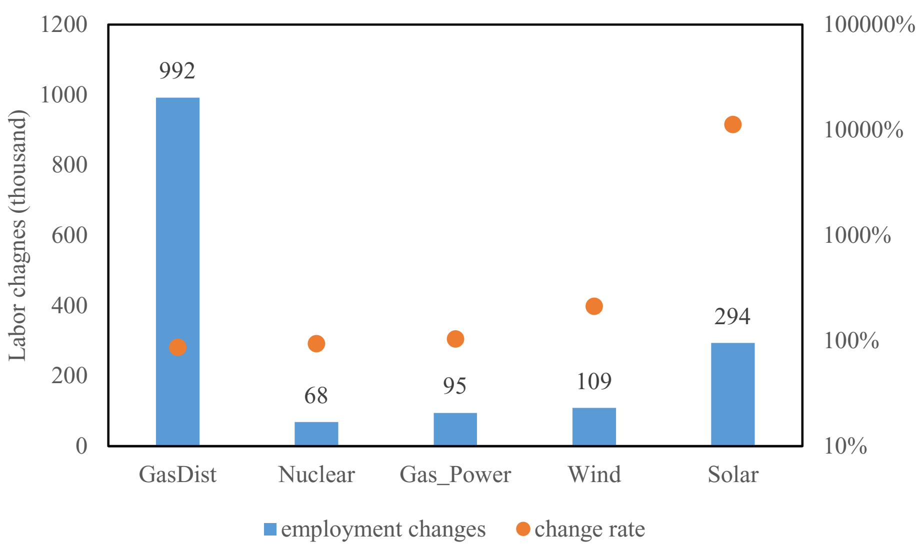

Fig. 6. Labor demand increase in LCD scenario compared with TE scenario.

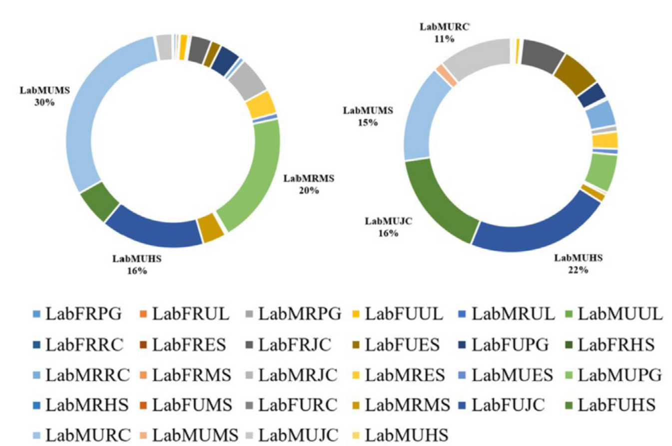

Fig. 7. Labor types in the coal (left), versus the solar and wind (right), sectors in 2050 in the LCD scenario.

Table 2
Labor demand in coal versus solar and wind sectors in 2050 in the LCD scenario (thousand).

	Coal	Solar power	Wind power
2012	4842.8	0.6	14.2
2050	1268.9	296.4	160.2

new energy industries and tertiary industries will flourish and attract agricultural workers. The significant loss of agricultural farmers will increase the proportion of capital and energy investment in the agricultural industry, which means the modernization of agriculture will continue to increase, and the income of agricultural employment will also increase. Second, in the second and tertiary industries, the employment opportunities for highly-educated people will increase, because demand for labor with a high education level in the emerging industries far exceeds that of the traditional industries. In contrast, workers with a low education level in urban areas will face increasingly serious challenges, which

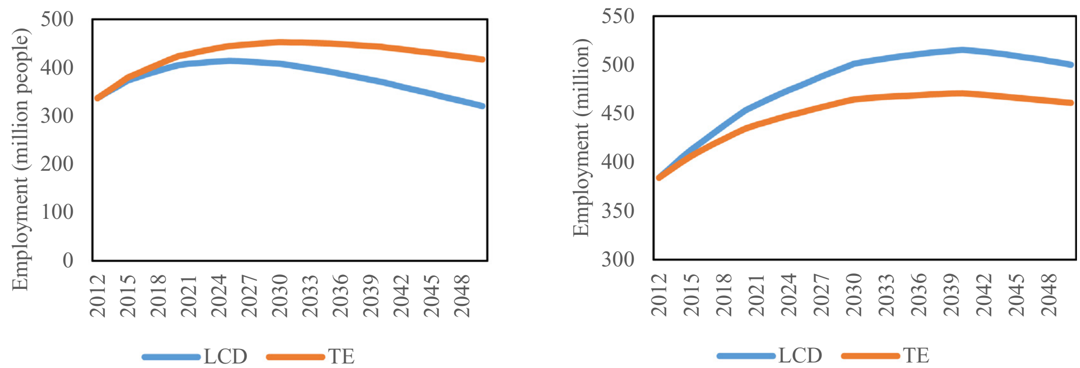

Fig. 8. Employment in the rural (left) and urban (right) regions.

will widen the gap between the poor and the rich in urban areas. The below shows results from the model.

4.4. Household income

To further identify the impact of changes in the labor market on household income, our study compares changes in the average income levels of urban and rural residents. The results show that in both scenarios, per capita income of urban and rural residents will maintain a growth trend, and will be stable after 2030. However, in the LCD scenario, as the number of workers engaged in agriculture decreases, the role of energy and capital in agricultural output grows, increasing the level of agricultural modernization and resulting in a faster (than the TE scenario) growth rate of per capita income in rural areas. The per capita income in rural areas reached 32,714 yuan RMB in 2050, which was 3.39 times that the rate of 2012 (Fig. 9). Particularly, in this scenario, the average household income of rural areas is higher than that of urban areas in 2050, suggesting that the problem of uneven development between urban and rural areas will be substantially reduced by 2050. Therefore, the role of low-carbon policies realized through the labor market will further stimulate the urbanization process, and at the same time promote the modernization of the agricultural industry, reducing or even completely solving the imbalance in urban and rural development.

On the other hand, the rapid development of urbanization poses challenges to the living conditions of urban residents. Due to the rapid development of emerging industries and the reduction in the traditional energy industry, employers with a high education level versus a low education level will face very different prospects. This will eventually widen the income gap among urban residents. Our study calculates and compares the income levels of the richest 20% of urban residents and the poorest 20% of urban residents (Fig. 10). In the LCD scenario, the per capita income of households at the bottom of the urban population is 530 yuan lower than in the TE scenario in 2050, while the income per capita of the urban upper class family is 5562 yuan higher than in the TE scenario. In both scenarios, urban residents' income will continue to grow until 2040, but will then decline after 2040. This will occur because China's GDP after 2040 will be stable, but the urbanization rate will continue to maintain a certain growth rate, resulting in a decline in the per capita income of urban residents. Therefore, the government should pay close attention to the problem of the polarization between rich and poor in the process of low carbon development and urbanization, and take measures to improve the living quality of the poor through taxation, public services, and promoting education.

5. Conclusions and discussion

5.1. Main findings and policy suggestions

This study examined the opportunities and challenges related to China's income gap as it moves toward achieving NDC targets from the labor market perspective. Our general finding is that China's low-carbon policy will lead to labor movements in energy-related industries from the traditional energy sectors to the renewable energy sectors. This will eventually lead to a reduction in the income gap between urban and rural residents, but it will also eventually cause an increase in the income gap among urban residents. Our research provides important policy recommendations for the government. First, our research reveals that under the existing energy structure, without policy intervention, China's carbon emissions will continue to grow, the country will be unable to achieve NDC targets, and peak carbon emissions will be 3.4 times the levels of 2012. This conclusion highlights the important role of low-carbon policies, especially in the renewable energy sectors.

Second, from a sectoral perspective, China's low carbon

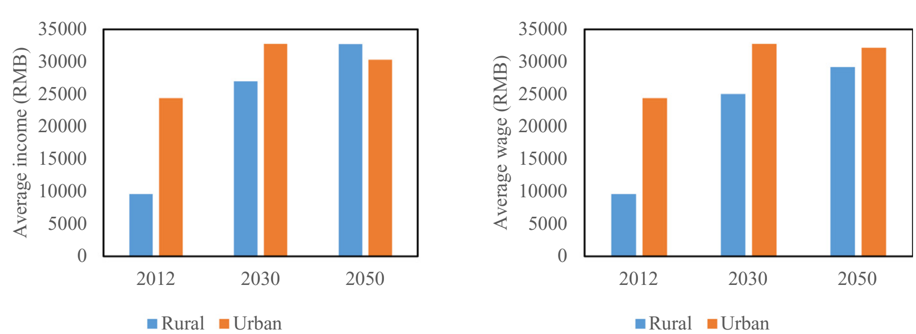

Fig. 9. Average per capita income in urban and rural regions in the LCD (left) and TE (right) scenarios.

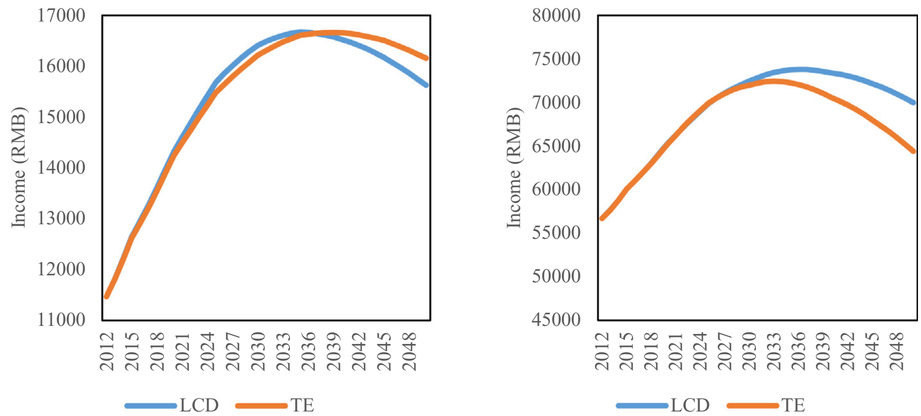

Fig. 10. Income per capita of the poorest 20% (left) and the richest 20% (right) in urban.

development will have the greatest impact on employment in the energy industries; it will negatively impact the traditional energy and positively impact the renewable power generation sectors. For the government, it is necessary to pay special attention to the unemployment risks that will be faced by workers in the energy sectors during the process of low-carbon development and provide adequate re-employment training for them to prevent structural unemployment problems.

Third, in the LCD scenario, the employment population in China will be transferred from rural to urban areas, and the urbanization rate will increase rapidly, reaching around 70% by 2050. The reduction of the rural population will bring new opportunities for the modernization of agriculture, increasing the income of rural residents. The problem of uneven development between urban and rural areas will be solved. By 2050, the per capita income in rural areas will reach 32,714 yuan, 3.39 times that of 2012. Promoting a balanced development of urban and rural labor markets will be an important co-benefit of low carbon policies.

At the same time, employers with a high education level versus a low education level will face very different prospects in urban areas. For example, the reduction in production in the coal sector alone will result in a loss of 3.57 million jobs, and workers with a high school education and below will account for 87.8% of these losses. In contrast, the development of renewable energy such as solar and wind power will increase the number of jobs for workers with a junior college education or above by 182 thousand. The income gap among urban residents is estimated to increase. By 2050, the per capita income of households at the bottom of the urban population will be 3.28% lower than in the TE scenario, while the per capita income of the upper class family will be 8.64% higher than in the TE scenario. At present, China's labor and urban migration phenomenon has created problems in the areas of social security, training and employment, children's schooling, and living conditions. In the future, such problems will continue. Policies such as the reform of the household registration system, an equal employment market, and a comprehensive social security system will be important for existing and new urban residents.

5.2. Limitations

This study provides an assessment of the income gap problem that China will encounter in the process of achieving NDC targets. We consider detailed economic structures, urbanization and different types of labor among sectors; but some limitations remain.

First, the model that we used disaggregated the labor types based on the empirical research data from 2012. Our estimates of demand for labor of different types are also based on this research, and we did not analyze potential future changes in labor demand. For example, the modernization of the agricultural sector may attract some high-educated workers from urban areas, which may have a certain impact on the study results. Second, this study lacks an analysis from the perspective of labor supply. For example, in the future, the improvement of education in China may lead to changes in the types of employed people and increase the degree to which labor supply matches employment demand. As another example, the aging problem that may arise in China in the future will also have a certain impact on the job market. Third, the understanding of the labor market in this study is based on existing technologies and perspectives. This study does not take into account the artificial intelligence technology that may appear in the future, due to the lack of reliable scenario prediction; this is an interesting and challenging area for future research.

Contribution of authors

Hai Huang and Can Wang designed the study and model development. Hai Huang conducted the model modification and simulation and wrote the draft. David Roland-Holst and Wenjia Cai contributed to the model development and modification.

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.

Acknowledgements

We gratefully acknowledge the comments and suggestions of anonymous reviewers. This research was funded by the National Natural Science Foundation of China (No. 71773062 and No. 71525007) and the National Social Science Foundation of China (No.17ZDA077).

Appendix A. Sectors in CGE model

No.	Sector	Abbr.	No.	Sector	Abbr.
1	Agriculture, forestry, farming & fishery products	AgFFF	22	Other manufacturing products	OthMfg
2	Coal mining products	Coal	23	Waste and scrap	Waste
3	Oil & natural gas products	OilGas	24	Metal products & repair	MachRep
4	Metal mining products	MetMin	25	Electricity, heat production	ElecDist
5	Non-metallic mining	NMetMin	26	Gas Production and Supply	GasDist
6	Food and tobacco	FoodPr	27	Water production and supply	WatDist
7	Textiles	Textile	28	Construction	Constr
8	Wearing apparel	Apparel	29	Wholesale and Retail	WhRetTr
9	Wood products and furniture	WoodPr	30	Transportation	TranspSrv
10	Paper products	PaperPr	31	Accommodation and catering	HotRest
11	Petroleum, coal & nuclear	RefPet	32	Information services	ICTServ
12	Chemical products	Chemical	33	Finance	Finance
13	Non-metallic mineral	NMetPr	34	Real estate	RealEst
14	Metal smelting and refining	Metals	35	Business Services	BusServe
15	Metal products	MetalPr	36	Research and technical	ResTech
16	General equipment	GenEqp	37	Environmental management	EnvServ
17	Special equipment	SpecEqp	38	Resident services, repairs	ResServ
18	Transportation equipment	TransEqp	39	Education	Education
19	Electrical equipment	ElecEqp	40	Health and social work	Health
20	Communications equipment	ICTEqp	41	Culture, sports, entertainment	RecEnt
21	Instruments and meters	PrecInst	42	Public administration	PubAdm

Appendix B. Production functions in CGE model

$$Y_i = \min\left(\frac{INT_{1,i}}{\psi_{1,i}^{INT}}, \frac{INT_{2,i}}{\psi_{2,i}^{INT}}, \ldots \frac{INT_{j,i}}{\psi_{j,i}^{INT}}, \frac{KLE_i}{\psi_{1,i}^{KLE}}\right) \tag{B.1}$$

$$INT_{j,i} = \psi_{j,i}^{INT} \times Y_i \tag{B.2}$$

$$KLE_i = \psi_{1,i}^{KLE} \times Y_i \tag{B.3}$$

$$P_i = (1 + tx_i) \times \left(\sum_j \psi_{j,i}^{INT} \times PA_m + \psi_{1,i}^{KLE} \times PKLE_i\right) \tag{B.4}$$

where.

Y_i = aggregate marketed quantity of domestic output of sector i
$INT_{j,i}$ = quantity of intermediate input from sector j to sector i
KLE_i = quantity of value added to sector i
P_i = aggregate market price of sector i
PA_m = domestic market price of non-energy commodity m
$PKLE_i$ = aggregate value added market price of sector i
$\psi_{m,i}$ = quantity of m per unit of aggregate output of sector i
$\psi_{KLE,i}$ = quantity of KLE per unit of aggregate output of sector i
tx_i = production tax rate of sector i

$$KLE_i = \left[\alpha_i^L \times E_i^{\frac{\sigma_i^{KLE}-1}{\sigma_{KLE,i}}} + \alpha_i^{VA} \times VA_i^{\frac{\sigma_i^{KLE}-1}{\sigma_{KLE,i}}}\right]^{\frac{\sigma_i^{KLE}}{1-\sigma_{KLE,i}}} \tag{B.5}$$

$$L_i = \left(\alpha_i^L \times \frac{PKLE_i}{PL_i}\right)^{\sigma_i^{KLE}} \times KLE_i \tag{B.6}$$

$$VA_i = \left(\alpha_i^{VA} \times \frac{PKLE_i}{PVA_i}\right)^{\sigma_i^{KLE}} \times KLE_i \tag{B.7}$$

$$PKLE_i = \left[\left(\alpha_i^L\right)^{\sigma_i^{KLE}} \times PL_i^{1-\sigma_i^{KLE}} + \left(\alpha_i^{VA}\right)^{\sigma_i^{KLE}} \times PVA_i^{1-\sigma_i^{KLE}}\right]^{\frac{1}{1-\sigma_i^{KLE}}} \tag{B.8}$$

where.

L_i = quantity of labor input to sector i
VA_i = quantity of value added to sector i
PL_i = market labor price of sector i
PVA_i = aggregate value added market price of sector i
α_i^L = share factor of labor in sector i
α_i^{VA} = share factor of value added in sector i
$\sigma_{KLE,i}$ = elasticity substitution coefficient between labor and value added

Appendix C. The average wage of different labor types

No.	Gender	Region	Education	Abbr.	Average wage (Yuan)
L1	Male	Urban	Unlettered	LabMUUL	23,431
L2			Elementary	LabMUES	26,275
L3			Middle school	LabMUMS	34,098
L4			High school	LabMUHS	39,976
L5			Junior college	LabMUJC	47,648
L6			Regular college	LabMURC	57,187
L7			Postgraduate	LabMUPG	93,353
L8		Rural	Unlettered	LabMRUL	17,891
L9			Elementary	LabMRES	21,849
L10			Middle school	LabMRMS	28,150
L11			High school	LabMRHS	30,022
L12			Junior college	LabMRJC	35,971
L13			Regular college	LabMRRC	38,878
L14			Postgraduate	LabMRPG	47,189
L15	Female	Urban	Unlettered	LabFUUL	14,356
L16			Elementary	LabFUES	18,451
L17			Middle school	LabFUMS	23,097
L18			High school	LabFUHS	31,570
L19			Junior college	LabFUJC	36,160
L20			Regular college	LabFURC	46,625
L21			Postgraduate	LabFUPG	68,316
L22		Rural	Unlettered	LabFRUL	12,910
L23			Elementary	LabFRES	16,950
L24			Middle school	LabFRMS	20,751
L25			High school	LabFRHS	23,483
L26			Junior college	LabFRJC	29,295
L27			Regular college	LabFRRC	33,715
L28			Postgraduate	LabFRPG	28,733

Appendix D. Disaggregated household typess

Abbr.	Description	Proportion
HHR1	Low income household in rural area	20%
HHR2	Lower middle income household in rural area	20%
HHR3	Middle income household in rural area	20%
HHR4	Upper middle income household in rural area	20%
HHR5	High income household in rural area	20%
HHU1	Low income household in urban area	20%
HHU2	Lower middle income household in urban area	20%
HHU3	Middle income household in urban area	20%
HHU4	Upper middle income household in urban area	20%
HHU5	High income household in urban area	20%

Appendix E. The proportion of different technologies in electric power sector

Year	Coal	Oil	Gas	Nuclear	Hydro	Wind	Solar	Biomass
2012	0.627	0.060	0.024	0.042	0.169	0.054	0.002	0.022
2013	0.620	0.057	0.025	0.043	0.168	0.058	0.007	0.021
2014	0.613	0.054	0.027	0.043	0.167	0.063	0.013	0.021
2015	0.606	0.051	0.028	0.043	0.166	0.068	0.018	0.020
2016	0.600	0.048	0.030	0.044	0.164	0.072	0.023	0.019
2017	0.593	0.045	0.031	0.044	0.163	0.077	0.029	0.019
2018	0.586	0.042	0.032	0.044	0.162	0.081	0.034	0.018
2019	0.579	0.039	0.034	0.045	0.161	0.086	0.039	0.017
2020	0.572	0.036	0.035	0.045	0.160	0.090	0.045	0.016
2021	0.566	0.033	0.037	0.045	0.159	0.099	0.050	0.016
2022	0.559	0.030	0.038	0.046	0.157	0.100	0.055	0.015
2023	0.552	0.027	0.040	0.046	0.156	0.104	0.061	0.014
2024	0.545	0.024	0.041	0.046	0.155	0.109	0.066	0.014
2025	0.538	0.021	0.042	0.047	0.154	0.113	0.071	0.013
2026	0.532	0.018	0.044	0.047	0.153	0.118	0.077	0.012
2027	0.525	0.015	0.045	0.047	0.151	0.122	0.082	0.011
2028	0.518	0.012	0.047	0.048	0.150	0.127	0.087	0.011
2029	0.511	0.009	0.048	0.048	0.149	0.131	0.093	0.010
2030	0.504	0.006	0.049	0.048	0.148	0.136	0.098	0.009
2031	0.495	0.006	0.050	0.050	0.147	0.138	0.105	0.009
2032	0.485	0.006	0.050	0.052	0.145	0.140	0.112	0.009
2033	0.476	0.006	0.050	0.054	0.144	0.142	0.119	0.010
2034	0.466	0.006	0.050	0.056	0.143	0.144	0.125	0.010
2035	0.457	0.006	0.050	0.058	0.142	0.146	0.132	0.010
2036	0.447	0.006	0.050	0.060	0.140	0.148	0.139	0.010
2037	0.437	0.006	0.050	0.061	0.139	0.150	0.146	0.010
2038	0.428	0.006	0.050	0.063	0.138	0.152	0.153	0.010
2039	0.418	0.005	0.050	0.065	0.137	0.155	0.159	0.010
2040	0.409	0.005	0.050	0.067	0.135	0.157	0.166	0.010
2041	0.399	0.005	0.050	0.069	0.134	0.159	0.173	0.010
2042	0.389	0.005	0.050	0.071	0.133	0.161	0.180	0.011
2043	0.380	0.005	0.050	0.073	0.132	0.163	0.187	0.011
2044	0.370	0.005	0.050	0.075	0.130	0.165	0.194	0.011
2045	0.361	0.005	0.050	0.077	0.129	0.167	0.200	0.011
2046	0.351	0.005	0.050	0.078	0.128	0.169	0.207	0.011
2047	0.342	0.005	0.051	0.080	0.127	0.171	0.214	0.011
2048	0.332	0.004	0.051	0.082	0.126	0.173	0.221	0.011
2049	0.322	0.004	0.051	0.084	0.124	0.175	0.228	0.011
2050	0.313	0.004	0.051	0.086	0.123	0.177	0.234	0.012

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