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Scenario Analysis of Carbon Emissions in the Energy Base, Xinjiang Autonomous Region, China

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Abstract: The realization of carbon emissions peak is important in the energy base area of China for the sustainable development of the socio-economic sector. The STIRPAT model was employed to analyze the elasticity of influencing factors of carbon emissions during 1990–2010 in the Xinjiang autonomous region, China. The results display that population growth is the key driving factor for carbon emissions, while energy intensity is the key restraining factor. With 1% change in population, gross domestic product (GDP) per capita, energy intensity, energy structure, urbanization level, and industrial structure, the change in carbon emissions was 0.80%, 0.48%, 0.20%, 0.07%, 0.58%, and 0.47%, respectively. Based on the results from regression analysis, scenario analysis was employed in this study, and it was found that Xinjiang would be difficult to realize carbon emissions peak early around 2030. Under the condition of the medium-high change rates in energy intensity, energy structure, industrial structure, and with the low-medium change rates in population, GDP per capita, and urbanization level, Xinjiang will achieve carbon emissions peak at of 626.21, 636.24, 459.53, and 662.25 million tons in the year of 2030, 2030, 2040, and 2040, respectively. At last, under the background of Chinese carbon emissions peak around 2030, this paper puts forward relevant policies and suggestions to the sustainable socio-economic development for the energy base area, Xinjiang autonomous region.

Keywords: carbon emissions; peak; energy base; STIRPAT model; policy implications

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) in its Fifth Assessment Report (AR5) confirms that the concentration of greenhouse gases has significantly increased since the Industrial Revolution, which accelerated the speed of climate change primarily characterized by global warming [1]. This will bring much more risks on the ecological safety, the food security, the safety of water resources, and so on, which seriously affect the development of the society and economy [2]. It is widely acknowledged that the significant increase in greenhouse gas concentrations is mainly due to the energy-related carbon emissions caused by human activities [2,3]. With the topic of global warming increasingly becoming a key environmental, political and economic issue, in order to mitigate the risks of global warming, the international community has made great efforts to reduce carbon emissions [4]. As an emerging market, though simultaneous development and accelerating industrialization, informatization, agricultural modernization, and urbanization, due to its long-term growth mode of high consumption, high pollution and low output, China has become the country with the largest carbon emissions [5]. In 2006, Chinese carbon emissions surpassed the United States of America (USA) and became the world's largest emitter [4]. In 2015, China accounted for 28.65% of the world's total carbon emissions, exceeding the sum of the USA (14.93%) and the European Union (9.68%), which was ranked second and third in the world, respectively (Global Carbon Project. http://www.globalcarbonatlas.org/en/ CO^2 emissions). With this, China has incurred huge attention from the world, which posed great international political pressures on China. In face of this situation, China pledged at the Copenhagen Climate Summit to increase the percentage of renewable energy in energy consumption structure to 15%, and to cut 40–45% of the energy intensity in 2020 when compared to the 2005 levels. Moreover, China promised at the Paris Agreement to increase the percentage of renewable energy in energy consumption structure to 20% and to cut 60–65% of the energy intensity in 2030 when compared to the 2005 levels, and make the best efforts to peak carbon emissions around 2030 [6]. How to realize this promise without compromising the socio-economic development has become an important issue that needs to be solved urgently. Therefore, empirical analysis and projection on carbon emissions are useful for the government to provide a theoretical and scientific basis for the sustainable development of low-carbon economy [4].

At present, the research on energy-related carbon emissions are mainly classified as the calculation of carbon emissions [7–9], analysis of decomposition methods and influencing factors [5,10,11], scenarios analysis and prediction of carbon emissions [12–15], the application of technology and policy simulation to reduce carbon emissions [16–18]. Moreover, the studies on influencing factors is a critical field to make projection and reduction policies for carbon emissions [5]. The research of carbon emissions' influencing factors are mainly focused on the social and economic fields, such as population scale [19,20], urbanization level [21,22], economic development [23,24], energy consumption structure [25], industrial structure [26], energy utilization efficiency [27], and so on. With the largest carbon emissions, studies have increased on the influencing factors in China. Economic growth, population size, and urbanization level have been confirmed to contribute the increase of carbon emissions, while reducing energy intensity, decreasing the percentage of coal in energy consumption structure, and adjusting industrial structure have been regarded as the main aspects to restrain carbon emissions [5,19,28,29]. As to the projections, it is mainly carried out by constructing the relationship model between carbon emissions and influencing factors, then using the scenario analysis to assess the projections. The projection models mainly include Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) [29], EKC (the Environmental Kuznets Curve) [30], IAMs (Integrated Assessment Model) [31], LEAP (Long-range Energy Alternative Planning) [32], GM (Grey Model) [33], and so on. The STIRPAT model is an effective method for quantitative analysis of influence factors on carbon emissions. It has advantages of comprehensive analysis and is considered as an established carbon emissions model which has been used widely [5,19,28,29].

Under the background of carbon emissions peak, several scholars focused on the STIRPAT model to analyze and project carbon emissions, thus assisting Chinese policymakers to formulate reasonable sustainable approach of socio-economic development. These studies suggested that Chinese carbon emissions will peak between 2020 and 2030 [4,14,15,34]. However, the national carbon emissions peak would not mean that provincial emissions status at the regional-level [5]. China is a vast country, which has great differences among provinces. There are huge discrepancies in the natural geographical condition, economic development, income level, population scale, development level, resident consumption tendency, and resource endowment among the different provinces [5]. For example, coastal areas are entering the post-industrialization stage, while western China are still in the stage of accelerating industrialization [35]. Developed areas have optimized the industrial structure to services, while central and western China are still dependent on the secondary industry [36].

Energy base areas are major exporters of energy, but central and eastern China are major importers of fossil fuel and electricity [37]. Some provinces have increased the percentage of renewable energy, while energy base areas remain dependent on coal consumption [38]. In this condition, there is great significance to forecast and analyze the provincial carbon emissions and put forward reduction strategy in consideration of huge variation across different provinces [5]. From the perspective of provincial analysis, Wen et al. found that under the medium growth rate of population, gross domestic product (GDP) per capita and urbanization, with reducing energy intensity and the adjustment of industrial and energy structure, the Beijing-Tianjin-Hebei area, the peak value of carbon emissions will appear between 2029–2045 [12]. Wu et al. found that in Qingdao, one of 36 low-carbon pilot cities, located in the Shandong province on the eastern coastal areas of China, the carbon emissions peak will appear between 2020 and 2025, under the condition of population control, reducing energy intensity and optimizing energy and industrial structure [6]. Zhang et al. found that if the population keep at a low growth rate, the GDP per capita and energy intensity kept at a high growth rate, the peak value of carbon emissions will appear at 2039 in Henan, the most populous province [15]. Cong et al. found that if the carbon intensity declines faster than the GDP per capita growth rate in Shanxi, the largest carbon emissions province in central China, the peak of carbon emissions will appear around 2030, if not, the carbon emissions will not peak before 2040 [39]. As a consequence, there are significant differences on the growth trends of carbon emissions at the provincial level. Moreover, the provincial differences pose a serious challenge to achieve the promise that China made at the Paris Agreement [10]. Therefore, it is necessary to understand the energy base area's carbon emissions and formulate a sustainable development road-map of carbon emissions peak.

In 2013, China promulgated the 12th five-year Energy Development Plan, which proposed to build five national comprehensive energy bases in Xinjiang autonomous region, Shanxi province, Ordos Basin, Eastern Inner Mongolia region, and southwestern China. Xinjiang is an important energy base in China, which contains the largest proven reserves fossil fuel, wind power and solar energy resources, the proved reserves of coal, gas, and oil accounting for 40%, 34%, and 30% of the national total resources, respectively [40]. Xinjiang, as a bridgehead of The Belt and Road, an undeveloped area in China, and is currently in the process of urbanization, agricultural modernization and accelerating industrialization. As an important energy base of "North–South Coal Transportation", "West–East Natural Gas Transmission Project", "North–South Oil Delivery", and "West–East Power Transmission Project", Xinjiang exports large amount of energy to other regions, which resulted in the huge transfer of carbon emissions [41]. Fossil fuel consumption has made great contributions to the socio-economic development in Xinjiang, which poses great challenges to sustainable development. Currently, the biggest dilemma is how to reduce carbon emissions without sacrificing at the expense of sustainable socio-economic developments in Xinjiang. This case study aims to go through scenario analysis and find out the pattern to realize carbon emissions peak as well as sustainable development in the socio-economic sector of Xinjiang. For the research of carbon emissions in Xinjiang, population scale and economic growth have been regarded as the key aspects contributing to the increase of carbon emissions, energy intensity and renewable energy are the key aspects for carbon emissions reduction [16,42]. Studies found that urbanization and industrialization also play significant roles to the change of carbon emissions in Xinjiang [5]. On the basis of existing research results, this research adopted STIRPAT model for the scenario analysis and considered the influencing factors such as population, GDP per capita, energy intensity, urbanization level, energy structure, and industrial structure. In order to verify the relationship between economic development and carbon emissions, we introduced the EKC model into STIRPAT model. Then, empirical analysis was performed between carbon emissions and the influencing factors. At last, by scenario analysis we put forward an optimized low-carbon development mode for the construction of socio-economic sustainable development in Xinjiang. This paper can serve as a reference for other energy base provinces or region with the similar situation.

Compared with other existing studies, there are two innovations or characteristics in this study. First, we verified whether an EKC relationship exists between economic development and carbon emissions in Xinjiang. Second, this study suggests a controlled way of socio-economic sustainable development for achieving carbon emissions peak in Xinjiang. The rest of the paper is organized as follows: Section 2 presents the study area, Section 3 provides the method and data, Section 4 provides the empirical analysis results, Section 5 explains the scenario analysis and projection results, Section 6 puts forth the discussions, and Section 7 presents the conclusions of this study.

2. Study Area

Xinjiang autonomous region (73°–96° E, 34°–50° N) is the largest province and accounts for one-sixth of the national land area in the northwest arid of China (Figure 1). It lies surrounded by the Kunlun, Tianshan, and Altay mountains. The Tien Shan mountain ranges divides the Xinjiang autonomous region into the Junggar and Tarim basins (Figure 1) [43,44]. The economy and population have grown rapidly in the recent years. The gross domestic product (GDP) hit 812.57 billion Yuan, and the GDP per capita reached 34,435 Yuan, which was less than 22% of the national level in 2015 [45]. The population was 23.59 million and urbanization level at 47.23% in 2015. The rapid socio-economic growth caused the huge demand of energy consumptions during 1990–2015. For example, the energy consumption was 659.67 million ton coal equivalent (Mtce) during 2011–2015 [45]. With the socio-economic development, energy consumption will reach new heights in the future. However, the huge demand of energy consumption will result in fast growth of carbon emissions. Xinjiang approximately accounted for 5% of the national total carbon emissions, but only accounted for 1.35% of Chinese total GDP in 2015. Carbon emissions per capita was 22.67 ton/person in Xinjiang, which was 2.7 times the national level in 2015 [9]. Therefore, there are huge challenges and pressures to the carbon emissions reduction while considering the fact that Xinjiang is a resource-dependent economic province, with rapid urbanization and industrialization, and an immense energy demand.

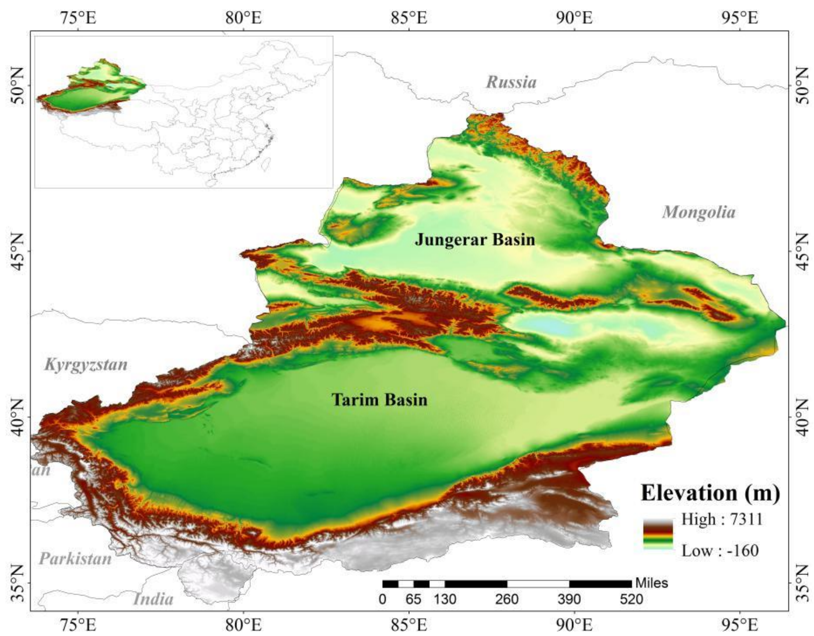

Figure 1. Location of Xinjiang autonomous region, China.

3. Data and Method

3.1. Data Sources

This study used three databases for carbon emissions projection in Xinjiang. We obtained the carbon conversion factors from the 2006 IPCC National Greenhouse Gas Inventories and China

Emission Accounts and Datasets (CEAD) [9]. The data of population, GDP per capita, energy intensity, urbanization level, the percentage of coal in energy consumption structure, and the percentage of secondary industry output to GDP from 1990 to 2015 were excerpted or calculated from the Xinjiang Statistical Yearbook [45]. Additionally, time series of economic data was corrected using the Consumer Price Index (CPI) in Chinese Yuan, with consideration of GDP constant prices in 2010 to evade the effect of inflation. Finally, the population and GDP projection in Xinjiang (2020–2050) were obtained from the Projection of Population and Economy to 2100 Under the Shared Socioeconomic Pathways in China [46,47].

3.2. Calculation of Carbon Emissions

According to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, total carbon emissions related to energy could be calculated in accordance with Equation (1):

$$C_t = \sum jE_t^j \times LCV_j \times CF_t^j \times O_j \tag{1}$$

where C_t denotes total carbon emissions in year t, E_t^j represents consumption of fuel j in year t, LCV_j denotes lower calorific value of fuel j, CF_t^j denotes carbon emissions factors of fuel j in year t, and O_j represents oxidation rate of fuel j. j represents different fossil fuel.

3.3. STIRPAT Model

The STIRPAT model derived from the IPAT model [48,49]. It describes the environmental effect of human activities [50] and is expressed as:

$$I = P \times A \times T \tag{2}$$

where I denotes environmental impact, P denotes the population, A represents the affluence, T denotes the technology level. However, the IPAT model cannot allow hypothesis testing [13], it also separates the other drivers behind environmental impact [51], and it assumes the elasticity of P, A, T is the same, which means P, A, T have the same contributions to environmental impact [52]. Reformulating the IPAT model to a stochastic form can overcome its limitations [53], which can be given as follows:

$$I = aP^bA^cT^de \tag{3}$$

where a is the model coefficient, b, c, d is the elasticity of P, A, T, e is the model random error. If a, b, c, d, e are all equal to 1, STIRPAT model can be seen as a same form of IPAT model [29]. In the empirical studies, taking Equation (3) logarithms, it can be transformed as the following:

$$\ln I = a + b \ \ln P + c \ \ln A + d \ \ln T + e \tag{4}$$

Besides population, affluence, and technology, there are many other social factors which also have the influence on environment. Many researchers have conducted to introduce additional social factors to STIRPAT model [54,55]. In this study, taking into account the specific circumstances and learning from previous studies, population, GDP per capita, energy intensity, urbanization rate, energy consumption structure, and industrial structure were introduced into STIRPAT model to analyze the impact of influencing factors on carbon emissions. Therefore, Equation (4) can be given as follows:

$$\ln I = a + b \ \ln P + c \ \ln A + d \ \ln T + e \ \ln E + f \ \ln U + g \ \ln S \tag{5}$$

where I represents carbon emissions (million ton), P denotes population (million person), A refers to GDP per capita (ten thousand Yuan/Per person), T denotes energy intensity (ton/ten thousand Yuan), E represents energy consumption structure (the percentage of coal in primary energy consumption structure), U represents urbanization rate, S is the industrial structure (the proportion of secondary industry output in GDP).

3.4. Environmental Kuznets Curve (EKC)

In order to testify the relationship between economic development and carbon emissions, we introduced the (EKC) into the STIRPAT model [56]. The EKC is a widely supported hypothesis as whether there exists an "inverse U-curve" relationship between economic development and carbon emissions or not [57]. In this study, the quadratic term of GDP per capita was introduced in STIRPAT model to test the existence of the EKC. Equation (5) can be given as follows:

$$\ln I = a + b\ln P + c\ln A + h\,(\ln A)^2 + d\ln T + e\ln E + f\ln U + g\ln S \tag{6}$$

where c represents elasticity of GDP per capita, h represents elasticity of quadratic term of GDP per capita. From Equation (6), we can obtained the elasticity (EE_{IA}) of GDP per capita to the carbon emissions [11].

$$EE_{IA} = c + 2\,h\ln A \tag{7}$$

If h was the negative value, it means that there is an "inverse U-curve" relationship between GDP per capita and carbon emissions in Xinjiang.

3.5. Ridge Regression

Ridge regression analysis was used to fit the STIRPAT model. Ridge regression analysis is an improved ordinary square regression method, where regression sensitivity is reduced by avoiding multiple collinearity of variables. Multiple collinearity refers to the high linear correlation between two or more explanatory variables in multiple regression models. It will lead to the expansion of the variance for the parameter estimation in the ordinary least square (OLS), making the regression model unstable and unreliability of the regression coefficients [29]. Ridge regression is one of the most effective methods to deal with multiple collinearity. Ridge regression can reduce large standard errors among the independent variables, through the tradeoffs of bias-variance in independent variables, the satisfactory biased estimation of smaller mean square error can be obtained [5,29].The usage of ridge regression is more flexible. This flexibility is the combination of qualitative and quantitative analysis, which plays an unique role in solving multiple collinearity [58].

4. Empirical Analysis

4.1. Features and Trajectories of Carbon Emissions and Influencing Factors

Carbon emissions were calculated based on Equation (1) for the period from 1990 to 2015. Figure 2 shows carbon emissions have an upward trend from 53.86 to 436.92 million ton during 1990–2015, with an annual increase of 8.8%. We can see the growth rate has accelerated during 2005–2015, which means, there must be huge pressures on carbon emissions reduction in the future.

Because the metric of each variable are differences, in order to cancel the metric differences, the standardized method (subtracting means and dividing by the standard deviations) is used to handle the data of carbon emissions and influencing factors in Xinjiang. Figure 3 shows the temporal variation of standardized carbon emissions and influencing factors. The trends of carbon emissions and influencing factors can be divided into two stages (Figure 3), namely slow growth during 1990–2004 and rapid growth during 2005–2015. During the period of 1990–2004, China fully carried out the reform and opening up policy. The economic development mode was transformed from planned economy to market oriented economy, and the growth rate of socio-economic development was relatively fast. Since the 1990s, Xinjiang implemented the advantage resource transformation strategy, which accelerated the process of industrialization, and the growth of energy consumption led to sustained increase in carbon emissions, with an average annual growth rate of 5.7%. It can be seen that energy intensity fluctuates obviously from 1990 to 2004. Energy structure and energy intensity increased slightly during 1994–1996, then continued to decline again after 1996. During the period of 1990–2004, carbon emissions and other influencing factors showed a slowly growth trend (Figure 3).

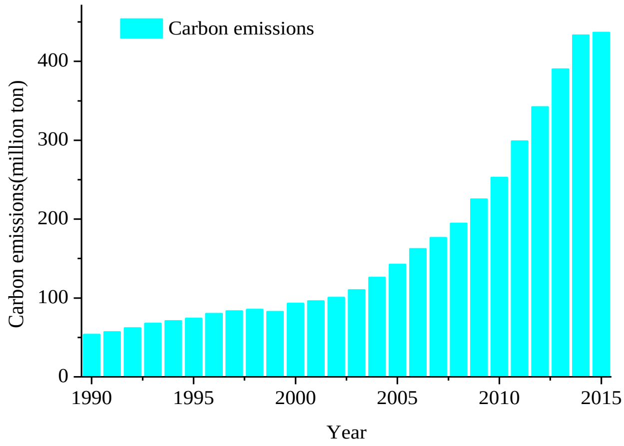

Figure 2. The changes of carbon emissions during 1990–2015 in Xinjiang.

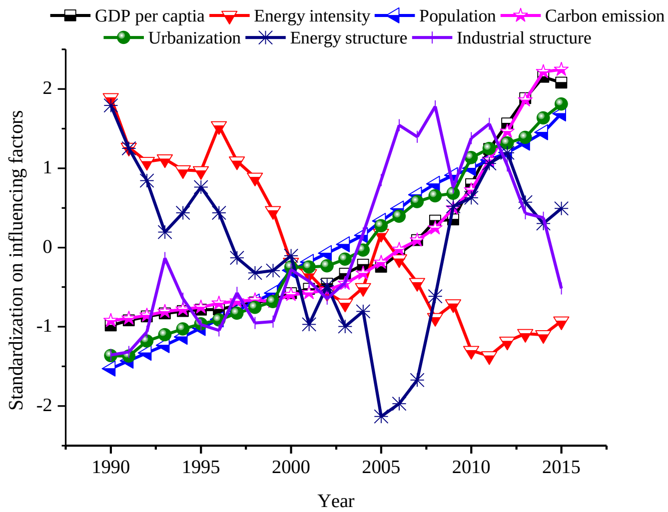

Figure 3. Trend of carbon emission and its driving factors after standardized during 1990–2015 in Xinjiang.

However, carbon emissions have increased relatively faster during 2005–2015, and influencing factors fluctuated obviously during this period. With the exploration and development of mineral resources and fossil energy, large numbers of large-scale heavy chemical projects started, the rapid development of industry led to the fast growth of energy-related carbon emissions in Xinjiang, with an average annual growth rate of 10.5% during 2005–2015. From 2005 to 2010, energy structure showed a fluctuating trend of rise and decline. Then after 2011, energy structure and the proportion of secondary industry output showed a downward trend and energy intensity increased slightly. China put forward and implemented the "Western Development Strategy" to improve the level of socio-economic development in the western region after 2001. The socio-economic development in Xinjiang was rapid after 2005. It can be seen that GDP per capita shows almost an exponential growth, and carbon emissions also increased rapidly during 2005–2015 (Figure 3). The population growth was also relatively fast, from 15.3 million persons (1990) to 23.6 million persons (2015), with an increase of 54%. It is not difficult to find that the urbanization level also showed a trend of sustained growth during 1990–2015. This is because of the economic development, which attracted much more rural people to employment in the urban area. It can also be seen that the proportion of secondary industry output showed an increasing trend during 1990–2010, but it decreased after 2011. The secondary industry was mainly composed of coal–chemical industries, iron and steel industries, power plants, and other industries. They are dominated by high energy consumption and high pollution. The implementation of coal–chemical industries and coal-power plants increased the consumption of coal. Due to the high energy consumption in coal–chemical industries and coal-power plants, the fluctuation of energy intensity was obvious after 2005 in Xinjiang.

4.2. Unit Root Test and Conintegration Test

In order to overcome the hypothesis of pseudo regression that may cause by direct regression of non-stationary in time series, it is necessary to test the stationarity of time series before establishing a regression model. The Augmented Dickey-Fuller (ADF) test is an effective method for the stationarity test of time series. To check whether the residual is stationary or not, if the residual does not have unit root, it is proved that there is a cointegration relationship between variables, and if there is a unit root, it is the opposite [59–62]. In the ADF test using Eviews9.0, the options 'trend' and 'intercept' should be added, the results show that at their first order difference of Augmented Dickey-Fuller test (Table 1), the ADF values of LnP, LnA, LnA^2, LnT, LnE, LnU, LnS, and LnI are smaller than the critical values at the 1% significant level, which indicating that the hypothesis can be rejected at least 99% confidence level. It indicates that data of LnP, LnA, LnA^2, LnT, LnE, LnU, LnS, and LnI are stationary at their first order difference. Therefore, this gives the indication that the variables LnP, LnA, LnA^2, LnT, LnE, LnU, LnS, and LnI are all integrated at the first order. Then, the cointegration relationship between carbon emissions and influencing factors were tested by Engle–Granger method. Using Eviews 8.0 software to carry out the cointegration test and obtained the unit root test results of the regression equation. The results show that the ADF test statistics of the residual term's time series is −5.706, which is smaller than the critical value of –3.788 at the 1% significance level, the null hypothesis of 'no cointegration' is rejected at 1% level because of trace statistics being more than the critical value of −3.788. Therefore, there is a cointegration relationship between time series of LnP, LnA, LnA^2, LnT, LnE, LnU, LnS, and LnI.

Table 1. Results of the Augmented Dickey-Fuller (ADF) test at first order difference.

	ADF	Test Critical Values (1%)	Prob. *
LnI	−6.79	−4.42	0.00
LnP	−7.70	−4.42	0.00
LnA	−7.04	−4.42	0.00
(LnA)^2	−5.31	−4.42	0.00
LnT	−7.65	−4.44	0.00
LnE	−8.63	−4.42	0.00
LnU	−8.41	−4.50	0.00
LnS	−6.60	−4.47	0.00

Note. * at the 1% significant level.

4.3. Ridge Regression Estimation

The regression analysis among variables were carried out by SPSS21.0 (Statistical Product and Service Solutions) statistical software, linking with carbon emissions and influencing factors from 1990 to 2010. As shown in Table 2, the ordinary least square (OLS) was used to make a regression analysis of the multicollinearity of independent variables in the model, then to evaluate their variance inflation factor (VIF). VIF is the most commonly used measurement of the multicollinearity of independent variables in the regression model. Generally speaking, if the VIF value is greater than 10, serious multicollinearity among variables is indicated [5,29,57].

Table 2 shows the results between dependent variable and independent variables by Equation (6). The R^2 correlation coefficient is 0.99, and the value of F-statistic is 153.3. Additionally, the VIF of all variables are far greater than 10, which means that there is severely multi-collinearity among independent variables. It further mentions that OLS results are not reliable to reflect the relationship between carbon emissions and influencing factors in Xinjiang.

Table 2. Ordinary Least Squares results.

	B	SE	T	Sig	VIF
LnP	1.96	1.53	1.28	0.22	324.31
LnA	−0.20	0.50	−0.41	0.69	669.89
LnA^2	0.36	0.14	2.55	0.02	220.14
LnT	−0.31	0.14	−2.19	0.05	40.55
LnE	0.29	0.36	0.81	0.43	14.88
LnU	−1.37	0.93	−1.47	0.17	197.12
LnS	0.45	0.27	1.65	0.12	14.32
Constant	7.68	1.59	4.84	0.00	

Note. R^2 = 0.99, F = 307.56, Sig. = 0.

Then, we used the ridge regression estimation to carry out regression analysis in this study. Because the ridge regression is a biased estimate, to retain as much information as possible, the K value should not be overly large, and the K value at when the ridge trace is basically stable should be used [5,29]. When the ridge parameter K was equivalent to 0.2, the coefficient of determination R^2 was 0.99, the regression coefficient of each explanatory variable was stabilized, and the corresponding regression analysis results are displayed in Table 3. The coefficients of explanatory variables all passed the significant test of 5%. We can see R^2 is 0.99, and the F value also allow the 1% significant test in Table 3. This means that the fitting of ridge regression estimation is accurate, and the Equation (6) can be expressed as:

$$\ln I = -0.72 + 0.80 \ln P + 0.19 \ln A + 0.28 (\ln A)^2 - 0.20 \ln T + 0.07 \ln E + 0.58 \ln U + 0.47 \ln S \quad (8)$$

Table 3. The results of ridge regression analysis (K = 0.2).

	B	SE(B)	Beta	T	Sig
LnP	0.80	0.05	0.20	14.14	0.00
LnA	0.19	0.01	0.21	18.07	0.00
LnA^2	0.28	0.04	0.14	5.77	0.00
LnT	−0.20	0.02	−0.19	−8.85	0.00
LnE	0.07	0.21	0.01	0.33	0.74
LnU	0.58	0.04	0.18	14.05	0.00
LnS	0.47	0.10	0.14	4.61	0.00
Constant	−0.72	1.11	0.00	−0.64	0.52

Note. R^2 = 0.99; F-statistic = 143.079; Sig = 0.

As shown in Table 3, population scale is the key factor for the increase of carbon emissions. When population increases by 1%, carbon emissions will increase by 0.80%. GDP per capita is another key factor influencing carbon emissions increase. If GDP per capita increases by 1%, carbon emissions increase by 0.19%. Energy intensity is the key factor contributing to carbon emissions reduction, as 1% decrease in energy intensity will lead to carbon emissions decrease by 0.20%. Energy structure, urbanization rate, and industrial structure are the other factors influencing carbon emissions, as 1% changes, 0.07%, 0.58%, and 0.47% will change in carbon emissions, respectively.

Clearly, we can see the $(\ln A)^2$ coefficient is positive in Table 3, which confirms that in the study period or in the most recent stage, there is no relationship between economic development and carbon emissions based on EKC in Xinjiang. Based on Equation (7) and Equation (8), the predicted elasticity coefficients for carbon emissions from energy consumption for GDP per capita increase from

10,000 yuan to 70,000 yuan, as described in Table 4. According to the absolute values of the coefficients, we can conclude that the elasticity coefficient of energy consumption (EE_{IA}) in Xinjiang increases as the GDP per capita increases. This is mainly because the increase of GDP per capita introduces higher levels of consumption per capita. Thus, energy consumption and carbon emissions also increase accordingly. As shown in Table 4, with the increase in GDP per-capita, the impact on carbon emissions is gradually increasing, which is determined by the current stage of economic development in Xinjiang. However, there was less variation in elastic coefficients of carbon emissions, Zhang et al. implies that the rapid increase in prosperity and the advance of science and technology will contributed significantly to reducing carbon emissions [11]. Wang et al. indicated that once the society becomes rich enough, people will pay more attention to the environment and put effort into new efficient low-carbon technology, so as to effectively use related approaches that greatly improve environmental issues [57]. Wang et al. suggests that economic growth is both a problem and a solution in terms of emissions. While emissions tend to increase during the early stages of economic growth, there comes a point when emissions begin to decrease as income increases [63]. Currently, Xinjiang is still in the stage of economic growth at the expense of environmental deterioration. As the most potential development region in western China, fast industrialization and urbanization will still lead to the increase of carbon emissions in Xinjiang. Therefore, Xinjiang needs to make great efforts to change the mode of economic growth and take a long way to realize sustainable socio-economic development.

Table 4. Elasticity coefficient of the gross domestic product (GDP) per capita influenced on carbon emissions.

A	10,000	15,000	20,000	25,000	30,000	35,000	40,000	45,000	50,000	55,000	60,000	65,000	70,000
$\boldsymbol{EE_{IA}}$	5.44	5.67	5.84	5.96	6.07	6.16	6.23	6.30	6.36	6.41	6.46	6.51	6.55
$\boldsymbol{\Delta EE_{IA}}$		0.23	0.16	0.12	0.10	0.08	0.07	0.06	0.06	0.05	0.05	0.04	0.04

Note. A is GDP per capita (Yuan/Person, constant prices in 2010), EE_{IA} is elasticity coefficient, ΔEE_{IA} is the variation value of elasticity coefficient.

4.4. Model Verification

In order to examine the accuracy of the STIRPAT model, the regression analysis among variables were carried out by SPSS21.0 statistical software, linking with carbon emissions and influencing factors from 1990 to 2010. Carbon emissions of Xinjiang from 2011 to 2015 were obtained based on Equation (8) and reserved for model verification. Figure 4 shows the calculated and simulated carbon emissions. The results illustrate that the simulated values were basically consistent with the calculated values from 2011 to 2015. The average relative error was 5.3% during 2011–2015. It implies that STIRPAT model can be used to project carbon emissions in Xinjiang.

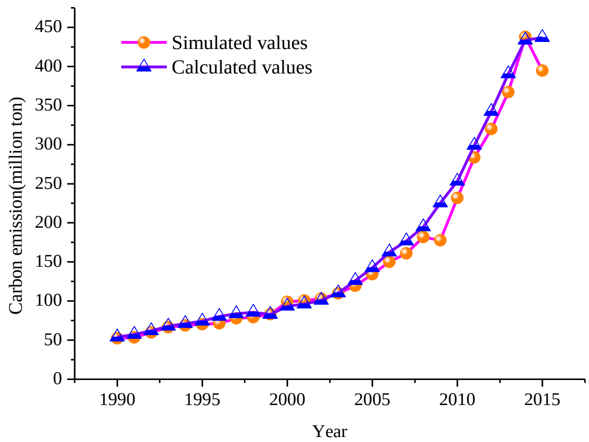

Figure 4. Calculated and simulated carbon emissions of during 1990–2015 in Xinjiang.

5. Scenario Analysis

5.1. Scenarios Construction

From the regression analysis results, influencing factors have significant effects on the carbon emissions change. The change rates of influencing factors might lead or delay the emergence of carbon emissions peak. Therefore, by means of scenario analysis, the effects of different parameter combinations on the future carbon emissions in Xinjiang were analyzed. Generally, population and economic growth will cause increase in carbon emissions. In contrast, reducing energy intensity, optimizing energy, and industrial structure are conducive to carbon emissions' reduction. Therefore, we separated influencing factors as two categories: positive factors (population, GDP per capita, urbanization level) and negative factors (energy intensity, energy structure, industrial structure). Further, we assembled influencing factors at different change rates for each scenario. In this study, we divided annual mean change rates of influencing factors during 2020–2050 into three levels: Low growth rate, medium growth rate, and high growth rate, which is denoted by "Low", "Medium", and "High", respectively (as shown in Table 5). The data of population and GDP per capita in Xinjiang during 2020–2050 were extracted from the literature [46,47].

Table 5. Parameters setting for scenario analysis from 2020 to 2050 in Xinjiang.

Growth Rate		**Time**						
		2020	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Population (P)/ (million person)	Low	23.92	24.80	25.44	25.96	26.39	26.66	26.75
	Medium	23.94	24.86	25.55	26.16	26.69	27.08	27.32
	High	24.07	25.15	26.05	26.88	27.67	28.35	28.93
GDP per capita (A)/ (ten thousand Yuan/Per person)	Low	4.51	5.55	5.71	5.63	5.73	5.52	5.46
	Medium	4.65	5.62	6.50	7.05	7.70	8.38	8.93
	High	4.68	5.64	6.67	7.67	8.82	9.89	10.54
Urbanization level (U)/%	Low	48.33	49.45	50.60	51.77	52.97	54.20	55.46
	Medium	49.52	51.91	54.43	57.06	59.82	62.72	65.76
	High	50.38	53.74	57.33	61.15	65.23	69.58	74.22
Industrial level (S)/%	Low	38.22	37.83	37.46	37.08	36.72	36.35	35.99
	Medium	37.83	37.08	36.35	35.63	34.92	34.23	33.55
	High	37.46	36.35	35.27	34.22	33.21	32.22	31.27
Energy intensity (T)/ (ton/ten thousand Yuan)	Low	1.52	1.37	1.24	1.12	1.01	0.92	0.83
	Medium	1.43	1.22	1.05	0.89	0.76	0.65	0.56
	High	1.28	0.97	0.74	0.56	0.43	0.33	0.25
Energy structure (E)/%	Low	61.63	57.73	54.07	50.65	47.44	44.44	41.62
	Medium	59.48	53.76	48.60	43.93	39.71	35.89	32.44
	High	56.21	48.02	41.03	35.05	29.94	25.58	21.86

As the Xinjiang's urbanization level was significantly lower than the national level during 1990–2015, we referred to the IIASA's (International Institute for Applied Systems Analysis) projection of Chinese urbanization rate as the high growth rate of urbanization during 2020–2050 [64]. By averaging the historical growth rates and with reference to the historical urbanization levels' change during 1990–2015, we calculated the medium and low annual growth rates of urbanization level for the period of 2020–2050 (as shown in Table 5) [45]. The growth rate of industrial structure for the period of 2020–2050 was obtained from literature [65]. By comparing energy intensity and the proportion of fossil fuel consumption in China, it is found that Xinjiang was much higher than the national level. We assumed that Xinjiang still has a long way to meet the intended National Determined Contribution (NDC) made by China at the Paris Agreement. Therefore, we set up Chinese intended NDC about energy intensity and energy structure at 2030 in the Paris Agreement as the high annual change rates to energy intensity and energy structure for the period of 2020–2050 in Xinjiang (as shown in Table 5). The medium and low annual growth rates of energy intensity and energy structure were calculated from historical data (1990–2015) in Xinjiang Statistical Yearbook [45].

In consideration of the above assumptions and combination of these influencing factors at different growth rates, we assembled in 16 scenarios as demonstrated in Table 6.

Table 6. Description of 16 scenarios.

Scenarios	Positive Factors			Negative Factors		
	Population (P)	GDP Per Capita (A)	Urbanization Level (U)	Energy Intensity (T)	Energy Structure (E)	Industrial Structure (S)
L-L	Low	Low	Low	Low	Low	Low
L-M	Low	Low	Low	Medium	Medium	Medium
M-L	High	High	Medium	Low	Low	Low
M-M	Medium	Medium	Medium	Medium	Medium	Medium
M-H	Medium	Medium	Medium	High	High	High
H-L	High	High	High	Low	Low	Low
H-M	High	High	High	Medium	Medium	Medium
H-H	High	High	High	High	High	High
LMHM	Low	Medium	Medium	Low	High	Medium
MHML	High	High	High	Medium	Medium	Low
HML	High	High	Medium	Medium	Medium	Low
LHML	Low	High	High	Medium	Medium	Low
HLMH	High	Low	Low	Medium	Medium	High
MHML	Medium	Medium	High	High	High	Medium
HMLM	High	Medium	Low	Medium	Medium	Medium
LMH	Low	Medium	Medium	Medium	Medium	High

5.2. The Projection of Carbon Emissions

Figures 5 and 6 shows the projection of carbon emissions under 16 scenarios from 2020 to 2050. It can be summarized in three patterns: Peak scenarios at 2030, peak scenarios at 2040, and scenarios without peak. It is clear that there are differences about carbon emissions in the peak scenarios, which could be arranged from small to large as "HLMH", "L-M", "LMH", "L-L" with the peak value of 459.53, 626.21, 636.24, and 662.25 million ton, with the corresponding peak time occurring at 2040, 2030, 2030, and 2040, respectively (Figure 6).

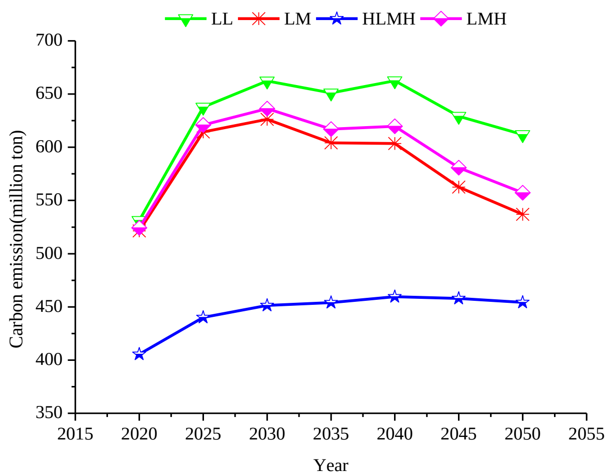

Figure 5. Peak scenarios of carbon emissions.

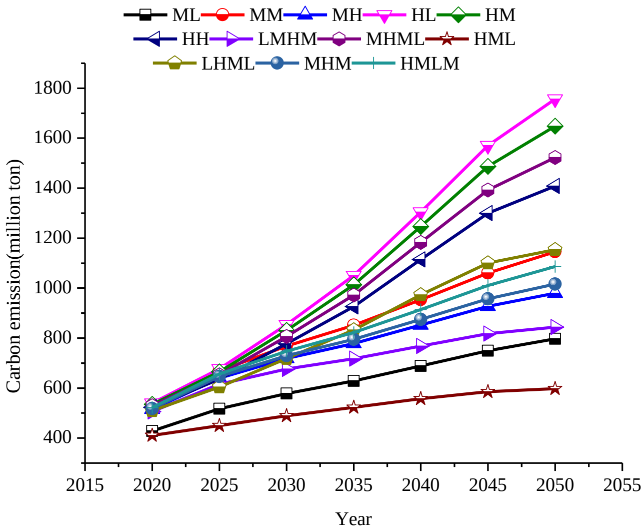

Figure 6. Scenarios without carbon emissions peak.

6. Discussion

Under the development patterns of scenario "HLMH" and "L-M", carbon emissions will be small and peak times occur at 2030 and 2040. However, these scenarios demand that Xinjiang should maintain a certain socio-economic growth rate. Clearly, these development patterns are counter to the future social and economic development trend of Xinjiang, because it optimizes the environment at the expense of improving the living standards and industrial structure. Under the development patterns of scenario "L-L", carbon emissions will be high and peak time occurs in 2040. However, this scenario demands that Xinjiang should maintain a low growth rate in socio-economic development. It is clear that this pattern is in opposition with the trend of economic, social, and environmental harmony and sustainable development, which is contrary to the trend of economic development in China. For the development pattern of scenario "LMH", carbon emissions peak will occur in 2030. This scenario demand that Xinjiang should maintain at a low growth rate in population and medium-high growth rates in socio-economic development and technological advances. After 2014, the aging process of population has been obviously accelerated and economic development has entered the new normal in China. In recent years, Xinjiang has carried out a supply-side structural reform to change the mode of economic growth through the rational allocation of resources, eliminate high energy-consuming production capacity, and optimize the industrial structure. Since 2015, the economic growth of Xinjiang has been dominated by the tertiary industry, the proportion of secondary industry' output has decreased significantly, and energy consumption structure has gradually transformed from high-carbon coal to low-carbon natural gas. Therefore, the development pattern of scenario "LMH" conforms to the requirement of sustainable development of the socio-economic sectors in Xinjiang, and it is a more feasible development pathway to achieve the peak of carbon emissions. It has been found that economic growth, population growth, and urbanization are the most influential driving factors to stimulate carbon emissions increase, the decline of energy intensity, adjustment of industrial structure, and optimization of energy structure are the effective ways to reduce carbon emissions. From the perspective of population factors, the influence of population scale is higher than that of urbanization. While under the condition of reasonably population control, the local government should pay a great of attention to the process of urbanization, which has its objective law and should not blindly seek its level. The process of urbanization should develop in harmony with economy and society. At the same time, Xinjiang should improve the quality of urbanization, especially improve the technical capacity of the labor force, prepare for the development of energy-saving industries, and improve the industrial structure.

Rapid economic growth leads to the increased demand for energy consumption, but economic growth can also by adjusting industrial structure and developing clean technologies to reduce energy intensity. Since Xinjiang is an important energy base region of energy production and power export, its industrial structure depends heavily on energy consumption. It is a key goal to improve the quality of economic development by promoting the effective transformation and technological progress from high energy consumption sectors to low energy consumption sectors in the secondary industry. At the same time, the development level of tertiary industry is relatively low, and the effect on reducing the intensity of regional carbon emissions is not obvious. Therefore, while on the condition of reducing the proportion of the secondary industry and increasing the proportion of the tertiary industry, Xinjiang should pay a great deal of attention to optimizing the internal structure of the tertiary industry, focusing on the development of the low-carbon industry of tertiary industry, improving the regional industrial structure, and reducing the energy intensity of industrial carbon emissions. From a technical standpoint, there is still a large space for the reduction of energy intensity. Therefore, local government can draw lessons on advanced energy consumption patterns from the developed countries to reduce carbon emission intensity. Due to the absolute dominant position of coal in energy consumption structure, the change of energy consumption structure seems to have little influence on carbon emissions, but in fact it has great potential in carbon emissions' reduction. In addition, energy structure has little effect on restricting carbon emissions, promotes the development of non-fossil fuel in the power plants, especially the development of wind and solar energy, and gradually develops wind and solar power plants.

7. Conclusions and Policy Implications

In this study, we used the STIRPAT model to explore the relationship between carbon emissions with population, GDP per capita, energy intensity, urbanization rate, energy and industrial structure in an energy base, Xinjiang autonomous region, China. On the basis of relevant data, combined with SPSS statistical software, we used the ridge regression method to fit the STIRPAT model. For the analysis of the relationship between carbon emissions and economic development, we tested the EKC hypothesis between carbon emissions and GDP per capita. Finally, based on the reliable fitting results and comparison verification, scenarios analysis was adopted to project carbon emissions and put forward relevant policy measures and suggestions to achieve sustainable socio-economic development.

Based on regression analysis, results show that there is non-existence of EKC hypothesis between economic development and carbon emissions in Xinjiang, the carbon emissions peak testified four scenarios during 2030–2040. The projection of carbon emissions can be classified into three categories: Peak scenarios at 2030, peak scenarios at 2040, scenarios without peak. Under the peak scenarios at 2030, peak value of the scenario "L-M" and "LMH" will emerge at 626.21 and 636.24 million ton, respectively. Under the peak scenarios at 2040, peak value of the scenario "L-L" and "LMHM" will emerge at 459.53 and 662.25 million ton, respectively. The carbon emissions peak of scenario "LMH" will occur at 2030, and it suits the requirement for the sustainable socio-economic development in Xinjiang. This scenario demand that Xinjiang should maintain at a low population growth rates and a medium-high growth rate in socio-economic development and technological advances.

In order to narrow the socio-economic gap with other inland provinces and realize leap-forward development in Xinjiang, Chinese central government asks 19 provinces and municipalities about "counterpart aid" to Xinjiang by the model of reconstruction on disaster areas after 2010. With the implementation of "counterpart aid" policy, large amounts of capital will be invested to Xinjiang in the future. In 2016, China promulgated the population policy of "comprehensive two-child". The population growth in Xinjiang is bound to continuously increase in the future. Xinjiang is a typical underdeveloped energy base in China, and economic development must to be the primary task in the foreseeable future. Based on the above-mentioned background of socio-economic development, carbon emissions will increase accordingly. Therefore, the focus of carbon emissions reduction and sustainable socio-economic development should maintain at a low population growth rate, keeping a reasonable growth rate in socio-economic development, reducing the energy intensity, significantly increasing the share of renewable energy in energy consumption structure, continuously reducing the percentage of coal consumption in energy consumption, and optimizing the energy consumption structure. At the same time, Xinjiang should make use of the geographical advantages of Eurasian center to develop tertiary industry and tourism, so as to optimize the industrial structure and reduce the dependency on secondary industry.

Author Contributions: All authors conceived, designed, and implemented the study. J.Q., G.M., and H.T. designed and carried out the study. J.Q. and M.Z. collected and analyzed data. Q.M. and K.B. improved the expression and grammar.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

IPCC	Intergovernmental Panel on Climate Change
AR5	Fifth Assessment Report (AR5)
USA	United States of America
STIRPAT	Stochastic Impacts by Regression on Population, Affluence and Technology
EKC	Environmental Kuznets Curve
IAMs	Integrated Assessment Model
LEAP	Long-range Energy Alternative Planning
GM	Grey Model
GDP	Gross domestic product
CEAD	China Emission Accounts and Datasets
CPI	Consumer Price Index
OLS	ordinary least square
VIF	variance inflation factor
IPAT	Impact = Population × Affluence × Technology
I	carbon emissions
P	population
A	GDP per capita
T	energy intensity
E	energy consumption structure
U	urbanization rate
S	industrial structure
EE_{IA}	elasticity of GDP per capita
SPSS	Statistical Product and Service Solutions
IIASA	International Institute for Applied Systems Analysis
ADF	Augmented Dickey-Fuller
NDC	National Determined Contribution

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