How Do the Population Structure Changes of China Affect Carbon Emissions? An Empirical Study Based on Ridge Regression Analysis

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Abstract: This study focuses on the impact of population structure changes on carbon emissions in China from 1995 to 2018. This paper constructs the multiple regression model and uses the ridge regression to analyze the relationship between population structure changes and carbon emissions from four aspects: population size, population age structure, population consumption structure, and population employment structure. The results showed that these four variables all had a significant impact on carbon emissions in China. The ridge regression analysis confirmed that the population size, population age structure, and population employment structure promoted the increase in carbon emissions, and their contribution ratios were 3.316%, 2.468%, 1.280%, respectively. However, the influence of population consumption structure (-0.667%) on carbon emissions was negative. The results showed that the population size had the greatest impact on carbon emissions, which was the main driving factor of carbon emissions in China. Chinese population will bring huge pressure on the environment and resources in the future. Therefore, based on the comprehensive analysis, implementing the one-child policy will help slow down China’s population growth, control the number of populations, optimize the population structure, so as to reduce carbon emissions. In terms of employment structure and consumption structure, we should strengthen policy guidance and market incentives, raising people’s low-carbon awareness, optimizing energy-consumption structure, improving energy efficiency, so as to effectively control China’s carbon emissions.

Keywords: carbon emissions; population structure; time series; ridge regression; China

1. Introduction

In the 21st century, global warming has become the most important challenge as an international environmental problem for mankind [1]. Greenhouse gas is considered to be the main cause of global warming, especially carbon dioxide [2]. Due to the sharp increase in energy consumption, carbon dioxide emissions accelerate global warming. In February 2020, the International Energy Agency (IEA) released the 2019 Global Carbon Emissions Report. According to the report, the global carbon emissions were about to be 33 billion tons in 2019.

With the development of the economy and the increasing energy consumption, China is also facing great pressure and challenges in the reduction of carbon emissions. From 2000 to 2013, China’s carbon dioxide emissions increased rapidly, with an average growth rate of 8.2% [3]. At the Copenhagen Climate Conference, the Chinese government made a commitment to reduce the carbon dioxide emissions per unit of GDP by 40–45% by 2020, compared with the statistics in 2005 [4]. China is the largest carbon emitter in the world, accounting for a quarter of global carbon emissions [5]. According to the data collected by the Global Carbon Atlas, by the end of 2017, China’s carbon emissions ranked first in the world, with a total of 9.839 billion tons, accounting for 27.2% of the total global carbon emissions. As the largest carbon dioxide emitter in the world, Chinese officials inferred
that the carbon dioxide emissions would reach a peak by 2030 at the 2015 Paris Climate Change Conference [6]. The next decade would be a critical period for China to fulfill its commitment to reaching peak carbon emissions [7]. Therefore, it is necessary to study the factors influencing carbon dioxide emissions and put forward suggestions.

According to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC), since the middle of the 20th century, nearly 90% of the greenhouse gas emissions have been caused by human daily activities [8]. Population factors have caused great pressure on the environment and became one of the main causes of environmental problems. In China, being the largest developing country in the world and with a large population, the growth of population has increased the burden on housing, transportation, water and electricity supply, education, and health facilities, leading to the continuous increase in energy demand and carbon emissions. Population has become a major driver of carbon dioxide emissions and energy footprints [9]. Asumadu-Sarkodie showed that there was evidence of a long-run equilibrium relationship from population to carbon dioxide emissions [10]. It explains the relationship between population and carbon dioxide emissions. The expansion of population size will increase carbon dioxide emissions over a long period. The impact on carbon emissions is generally reflected in production and consumption behavior, which is closely related to the changes in population structure. Relevant studies on carbon emissions in European countries have shown that population structure changes were one of the determinants of carbon dioxide emissions [11]. Therefore, it is very important to explore the influences of population structure changes on carbon emissions in China. So, this paper will analyze the relationship between population structure changes and carbon emissions from the four aspects of population size, the age structure of the population, the consumption structure of the population, and the employment structure of the population with time-series data from 1995 to 2018. Based on the framework of the multiple regression model, this study uses the ridge regression analysis method to analyze the impact of many variables on carbon emissions.

2. Literature Review

2.1. The Impact of Population Size on Carbon Emissions

Many scholars have studied the relationship between population size and carbon emissions from different perspectives. From the global perspective, some scholars indicated that population growth was the main reason for the rise of global carbon dioxide emissions. With the continuous increase of population, the carbon dioxide produced by residents in their daily life also increased [12,13]. Based on the investigation of global data from 1975 to 1996, it was found that every 1% increase in the amount of population would lead to a 1% increase in carbon emissions [14]. These results all indicate that the expansion of population size will increase carbon dioxide emissions. From the perspective of countries, some scholars believed that the impact of population size on carbon emissions was quite different in countries with different levels of development. Such as, compared with developed countries, the population changes in developing countries had a more significant impact on carbon emissions [14]. For carbon emissions, the sample of countries in Asia experienced the largest percent increase, followed by countries in Latin America, Africa, and lastly the sample of relatively affluent countries in Europe, North America, and Oceania combined [15]. The population growth in China and India was the main factor affecting the changes in carbon emissions [16]. For China, although the population size is different in different regions, its impact on carbon emissions is the same. The population growth in Taiwan was the driving force of carbon emissions, and the reduction of population growth would reduce carbon emissions by 16–29% [17]. Chen and Zhu analyzed the relevant survey data of Fujian Province from 2000 to 2009 and decomposed the carbon emission impact index with Kaya identity. It was found that population growth could increase carbon emissions [18]. Based on the STIRPAT model, Yu Mingcheng studied the influencing factors of carbon dioxide emissions in Shanxi Province. The results showed that population had the greatest impact on carbon dioxide emissions in Shanxi Province [19].
The above research results show that both analyzed from the global perspective or national perspective, it has been confirmed that the expansion of the population size will promote the increase of carbon emissions, thereby exacerbating global warming.

2.2. The Impact of Age Structure on Carbon Emissions

With the development of the economy, in the process of population growth, the changes of population structure have affected the economic growth, so Warren Thompson put forward the theory of demographic transition in the early 20th century. The process of demographic transition will form a population age structure conducive to economic development, and the social dependency ratio is relatively low in a period of time, which will last for a long time [20]. Demographers call this period the "demographic dividend". Bloom and Cooper pointed out that if most of a nation’s population falls within the working ages, the added productivity of this group can produce a “demographic dividend” of economic growth [21]. The demographic transition resulted in its working-age population growing at a much faster rate. Thereby expanding the per capital productive capacity of economies [22]. Cai Fang showed that the demographic dividend has formed a key period of relatively rich labor resources and sustainable economic development [23]. The high proportion of labor force ensures the demand of labor force in economic growth. Economic development will inevitably bring energy consumption, so the working-age population can affect carbon emissions.

On the relationship between age structure and carbon emissions, some scholars found that the change in age structure was the main driving force for the increase in carbon dioxide emissions [24]. The change of age structure could lead to the increase of carbon emissions and the impact of different age periods on carbon emissions were different [25]. Some studies indicated that the high proportion of the working-age population could bring greater energy consumption and higher carbon emissions [26,27]. The proportion of the working-age population (15–64 years old) had a negative correlation with carbon dioxide emissions in high-income countries, while it had a positive correlation in other income level countries [28]. For example, the proportion of the 35-to-64-year-old population in developed countries was negatively correlated with carbon emissions, the greater the proportion was, the less carbon dioxide produced [29]. For the population over 65 years old, there was a positive correlation between population aging and carbon emissions, and the acceleration of population aging would promote the increase of carbon emissions [30]. However, some scholars have shown that there were some regional differences in the impact of population aging on carbon emissions. For example, there was a significant inverted U-shaped curve relationship between population aging and carbon emissions, and the eastern region had a positive impact on carbon emissions, while the central and western regions had a negative impact [31]. Dalton used PET (Population, Environment, Technology) model and found that population aging had an inhibitory effect on carbon emissions in United States [32]. Similarly, Kim also confirmed that the population aging of Korea would reduce carbon dioxide emissions, and every 1% increase in the proportion of the elderly population would reduce carbon dioxide emissions by 0.4% [33]. In general, the impact of different age structures on carbon emissions in different countries is different. In China, there are few studies on the relationship between the proportion of the working-age population and carbon emissions, which needs further study.

2.3. The Impact of Resident Consumption and Employment Structure on Carbon Emissions

Some scholars indicated that the consumption of urban residents was the most significant factor leading to the increase of direct and indirect carbon emissions, and both showed a significant upward trend [34,35]. The carbon consumption of Chinese residents (rural and urban) grew steadily. The annual carbon consumption by urban and rural residents increased at a rate of 9.94% and 0.81%, respectively [36]. The regional differences in consumption rate and consumption structure would also have an indirect impact on carbon emissions [37]. In China, the residents’ consumption level in Beijing had a significant
impact on carbon emissions, and the elasticity coefficient fluctuated greatly [13]. As for the research on the relationship between employment structure and carbon emissions, some scholars believed that the increase of employment scale generally improved the level of carbon emissions of various industries, and had a positive role in promoting the scale of carbon emissions [38]. The industrial industry was the main driving force for carbon dioxide emissions, we should harmonize industrial development and carbon dioxide emission reduction [39]. Although the change of industrial structure was not the most important factor, it was one of the main driving forces of carbon dioxide growth [40]. Upgrading and optimizing the industrial structure was good for reducing carbon emission intensity [41].

In summary, many scholars have studied the relationship between population factors and carbon emissions in different aspects. Most scholars only studied one single influencing factor in the population structure, while there were few related studies to the impact of comprehensive factors within the population structure on carbon emissions. In addition, although population factors will affect carbon emissions, we cannot be sure which population factor is the most significant factor affecting carbon emissions. According to the degree of impact, how these population factors affect carbon emissions. There are still few studies and references on this aspect. Considering the complexity and diversity of population structure change, this paper will analyze the impact of population structure change on carbon emissions from the perspective of comprehensive influencing factors. As the largest population country in the world, the population of China will reach 1.4 billion by 2020, and its population structure is also diverse. Sofia showed that efficient mitigation strategies should be implemented for substantial environmental and health co-benefits [42]. Therefore, this paper selects the relevant data from 1995 to 2018 in China to study how population structure changes affect carbon emissions. According to the research results, one can formulate feasible carbon emission reduction policies, which provide a theoretical reference for China’s future low-carbon development. Meanwhile, it has practical significance for realizing carbon emission reduction goals and developing the low-carbon economy of China.

3. Materials and Methods

3.1. Model Specification

In this paper, the main content to be tested is the dynamic relationship of China’s carbon emissions and population size, age structure, employment structure, and consumption structure.

Firstly, we constructed a multiple regression model:

$$ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \mu $$

(1)

In order to reduce the influence of heteroscedasticity on the model and reduce the error in data processing, we took the logarithm of every variable of the model.

The model is as follows:

$$ \ln Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \mu $$

(2)

where $Y$ represents China’s carbon dioxide emissions; $X_1$ represents population size; $X_2$ represents population age structure, expressed by the proportion of the working-age population (15–64 years old); $X_3$ represents population consumption structure, expressed by the Engel coefficient; $X_4$ represents population employment structure, expressed by the proportion of employees in the secondary industry. $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients to be estimated, $\mu$ is the random error term.

The specific variables are defined in Table 1.
Table 1. Definitions and units of core variables.

| Codes | Variables                              | Definition                                               | Unit        |
|-------|----------------------------------------|----------------------------------------------------------|-------------|
| Y     | Carbon emissions                       | Carbon dioxide emissions                                  | \(10^4\) tons |
| \(X_1\) | Population size                        | Population total                                         | \(10^4\) persons |
| \(X_2\) | Population age structure               | The proportion of working-age population                  | %           |
| \(X_3\) | Population consumption structure       | The Engel coefficient                                     | %           |
| \(X_4\) | Population employment structure        | The proportion of employees in the secondary industry     | %           |

3.2. The Explanation of Core Variables

The variables are explained briefly as follows:

Carbon emissions: Carbon emissions mainly refer to the emission of greenhouse gases. Among the greenhouse gas emissions, the contribution of carbon dioxide to the greenhouse effect reaches 60%, and the content of carbon dioxide in the atmosphere is the highest. So, it is urgent to reduce and control carbon dioxide emissions.

Population size: Population size is the most important factor influencing carbon emissions. The population has an incremental effect on carbon dioxide emissions. It means that the larger the population size is, the more energy is used and consumed, and the greater carbon dioxide emissions are produced in China.

Population age structure: Due to the continuous growth of the number and proportion of the working-age population (15–64 years old) and the sufficient supply of labor resources in China, the consumption of energy resources increased gradually. Meanwhile, it promotes the expansion of production scale and leads to an increase in the scale of carbon dioxide emissions.

Population consumption structure: The Engel coefficient represents the consumption structure of residents. It is one of the main standards to measure the wealth of a family or a country. It shows that the consumption of food is smaller than the consumption in other aspects, which indirectly affects carbon dioxide emissions. The Engel coefficient is inversely proportional to the level of economic development. The lower the Engel coefficient is, the higher the economic development. Economic development can promote carbon emissions. So, if the Engel coefficient decreased, carbon emissions will increase.

Population employment structure: To a certain extent, the proportion of employees in the secondary industry reflects the degree of industrialization of the country. If the proportion of the industry becomes larger, the industrialization degree is greater. Industrial carbon emission is an important part of carbon emissions, therefore, the proportion of employees in the secondary industry has an indirect impact on carbon emissions.

3.3. Calculation of \(CO_2\)

The China Statistical Yearbook does not provide the statistical data of carbon dioxide emissions directly, and the calculation methods in relevant literature are not the same, so this paper uses the carbon dioxide emission calculation method of Du [43]. According to the carbon dioxide emission coefficients published by IPCC [44] and the National Coordination Committee Office on Climate Change and Energy Research Institute under the National Development and Reform Commission [45], energy consumption is divided into seven types: coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas. In order to estimate the carbon dioxide emissions more comprehensively, the carbon dioxide emission from cement production is also estimated.

The calculation formula to estimate the carbon dioxide emissions is as follows:

\[
CO_2 = \sum_{i=1}^{7} EC_i = \sum_{i=1}^{7} E_i \times CF_i \times CC_i \times COF_i \times 3.67
\]  

(3)

where \(i\) represents the indicator of different types of fossil fuel; \(EC\) represents the quantity of \(CO_2\) emissions from all seven types of fossil fuel consumption; \(E_i\) represents the total consumption of fuel; \(CF_i\) represents calorific value; \(CC_i\) represents the carbon content; \(COF_i\) represents the carbon dioxide factor.
represents oxidation factor; 3.67 is the carbon dioxide gasification coefficient. The gasification coefficient of carbon dioxide is the ratio of the mass after the carbon is completely oxidized to carbon dioxide to the mass before (i.e. 44:12), which is a standard amount of 3.67; $CF_i \times CC_i \times COF_i$ represents the carbon emission coefficient; $CF_i \times CC_i \times COF_i \times 3.67$ represents the carbon dioxide emission coefficient.

The formula for calculating carbon dioxide emissions from the cement production process is as follows:

$$CC = Q \times EF_{cement}$$

(4)

where $CC$ represents carbon dioxide emissions from cement production process; $Q$ is the cement production, $EF_{cement}$ is the carbon dioxide emission coefficient for the cement production process.

The carbon dioxide emission coefficients of various emission sources are shown in Table 2.

**Table 2.** Carbon dioxide emission coefficients of various energy sources.

| Energy Source | Carbon Content (TC/TJ) | Calorific Value (TJ/10^4 tons or TJ/10^8 m^3) | Carbon Oxidation Factor | Carbon Emission Coefficient (TC/T or TC/10^8 m^3) | CO\(_2\) Emissions Coefficient (TC/T or TC/10^8 m^3) |
|---------------|------------------------|---------------------------------------------|------------------------|---------------------------------------------|---------------------------------------------|
| Coal          | 27.280                 | 178.240                                     | 0.923                  | 0.449                                       | 1.647                                       |
| Coke          | 29.410                 | 284.350                                     | 0.928                  | 0.776                                       | 2.848                                       |
| Gasoline      | 18.900                 | 448.000                                     | 0.980                  | 0.830                                       | 3.045                                       |
| Kerosene      | 19.600                 | 447.500                                     | 0.986                  | 0.865                                       | 3.174                                       |
| Diesel Oil    | 20.170                 | 433.300                                     | 0.982                  | 0.858                                       | 3.150                                       |
| Fuel Oil      | 21.090                 | 401.900                                     | 0.985                  | 0.835                                       | 3.064                                       |
| Natural Gas   | 15.320                 | 3893.100                                    | 0.990                  | 5.905                                       | 21.670                                      |
| Cement        | -                      | -                                           | -                      | -                                           | 0.527                                       |

Note: The data from IPCC and the National Coordination Committee Office on Climate Change and Energy Research Institute of the National Development and Reform Commission.

4. Data Sources and Description
4.1. Data Sources

The fossil energy data are selected from China Energy Statistical Yearbook, the data of population, the proportion of the working-age population, the Engel’s coefficient, and the proportion of employees in the secondary industry are selected from the China Statistical Yearbook. The carbon dioxide emissions coefficients are from IPCC and the National Coordination Committee Office on Climate Change and Energy Research Institute of the National Development and Reform Commission [44,45].

4.2. Data Description

Figure 1 shows the changes in China’s population from 1995 to 2018. In terms of the population size, the natural growth rate of China’s population is subject to domestic family planning policy. It reached 1.060% in 1995 and has been declining since 1995. In 2006, it dropped to 0.529%. From 2006 to 2015, it has been in a stable state, the growth rate fluctuated between 0.497% to 0.529%. After reaching a peak in 2016, it began to decline. Although the natural growth rate has shown a downward trend in the past 24 years, the average annual net increase is about 7.674 million persons.
4.2. Data Description

Figure 1 shows the changes in China’s population from 1995 to 2018. The natural growth rate of China’s population is subject to domestic family planning policy. It reached 1.060% in 1995 and has been declining since 1995. In 2006, the policy became even more strict, and the growth rate dropped to 0.529%. From 2006 to 2015, it has been in a stable state, the growth rate fluctuated between 0.497% to 0.529%. After reaching a peak in 2016, it began to decline. Although the natural growth rate has shown a downward trend in the past 24 years, the average annual net increase is about 7.674 million persons.

From Figure 2, it can be seen that during the period of 1995–1999, carbon dioxide emissions increased from 2.733 billion tons in 1995 to 9.481 billion tons in 2018, with an average annual growth rate of 5.56%, and an increase of approximately 2.47 times. The trend of carbon dioxide emissions and the proportion of the working-age population shows the changes in China’s population from 1995 to 2018. In terms of the proportion of the working-age population (15–64 years old) and carbon dioxide emissions from 1995 to 2018. During the period of 1995–2010, the proportion of the working-age population showed an upward trend, reached 74.5% in 2010, and then showed a slow downward trend. China’s carbon dioxide emissions increased from 2.733 billion tons in 1995 to 9.481 billion tons in 2018, with an average annual growth rate of 5.56%, and an increase of approximately 2.47 times. From Figure 2, it can be seen that during the period of 1995–1999, carbon dioxide emissions are in a stable stage, and from 2000 to 2013, they are in a rapid growth stage, and gradually tend to be stable from 2013 to 2018.

Figure 2 illustrates the changing trend of the proportion of China’s working-age population (15–64 years old) and carbon dioxide emissions from 1995 to 2018. During the period of 1995–2010, the proportion of the working-age population showed an upward trend, reached 74.5% in 2010, and then showed a slow downward trend. China’s carbon dioxide emissions increased from 2.733 billion tons in 1995 to 9.481 billion tons in 2018, with an average annual growth rate of 5.56%, and an increase of approximately 2.47 times. From Figure 2, it can be seen that during the period of 1995–1999, carbon dioxide emissions are in a stable stage, and from 2000 to 2013, they are in a rapid growth stage, and gradually tend to be stable from 2013 to 2018.

Figure 3 describes the changing trend of the Engel coefficient from 1995 to 2018. Engel coefficient reflects the ratio of food expenditure to total consumption expenditure, which reflects the consumption structure of residents. The lower the coefficient is, the less the residents spend on food and the higher their living standards are. From 1995, the Engel coefficient has been decreasing year by year, which showed that China’s economy increased year by year.
Figure 3. The trend of the Engel coefficient.

Figure 4 shows the changing trend of the proportion of employees in the secondary industry. From the perspective of population employment structure, the proportion of employees in the second industry increased gradually and maintained a long-term balanced and stable state. After reaching a peak of 232 million in 2012, the number of employed people in China’s secondary industry has been decreasing for six years. The proportion of employees in secondary industry in China gradually decreased from 30.3% in 2012 to 27.57% in 2018. The secondary industry reflects the industrialization degree of a region or country. The higher the proportion of employees is in the industry, the higher the degree of industrialization is.

Figure 4. The trend of the proportion of employees in the secondary industry.

5. Empirical Results

The stationary time series is the premise of regression analysis, because, for a non-stationary time series, the traditional measurement methods may appear spurious regression phenomenon. So, it is important to test the stability of these time series before estimating the model. For non-stationary time series, if the cointegration test shows that there is a cointegration relationship between them, the regression results are also meaningful. In addition, if there is multicollinearity between independent variables, the variance of estimated parameters of the regression equation will be large, which will also affect the accurate judgment of population parameters. Therefore, it is necessary to test the multicollinearity of the variables. In this paper, the ADF unit root test was used to test the logarithmic series of each variable.

Table 3 shows the results of the ADF unit root. The logarithmic series of population size, the proportion of the working-age population, and the Engel coefficient were all sta-
tionary time series. The logarithmic series of carbon dioxide emissions and the proportion of employees in the secondary industry were all first-order single integer series.

**Table 3.** The results of the ADF unit root.

| Variables  | t-Statistic | 1%  | 5%  | 10% | Conclusion |
|------------|-------------|-----|-----|-----|------------|
| \(\Delta \ln Y\) | -1.721     | -2.674 | -1.957 | -1.608 | stable     |
| \(\ln X_1\)   | -10.971    | -4.416 | -3.622 | -3.249 | stable     |
| \(\ln X_2\)   | -2.22      | -2.699 | -1.961 | -1.607 | stable     |
| \(\ln X_3\)   | -3.279     | -2.669 | -1.956 | -1.608 | stable     |
| \(\Delta \ln X_4\) | -1.694 | -2.674 | -1.957 | -1.608 | stable     |

Note: \(\Delta\) refers to 1st differences, SIC is the criterion to determine the lag term.

Table 4 shows the results of the ADF unit root of residual. This paper used the EG (Engle–Granger) two-step method to test the cointegration of the logarithmic series of carbon dioxide emissions and the proportion of employees in the secondary industry. These two variables were regressed to get the residual sequence, and the residual was tested by ADF unit root test, at the significance level of 1%, the t-statistic was -3.116, which was less than the corresponding critical value, therefore, the original hypothesis was rejected. The results showed that the residual sequence had no unit root, was a stationary time series, and had a (1,1) order cointegration. It showed that there was a cointegration relationship between carbon dioxide emissions and the proportion of employees in the secondary industry. Also, there was a long-term equilibrium relationship between them.

**Table 4.** The results of the ADF unit root of residual.

| Variables | t-Statistics | 1%  | 5%  | 10% | Conclusion |
|-----------|--------------|-----|-----|-----|------------|
| \(E_t\)  | -3.116       | -2.674 | -1.957 | -1.608 | Stable     |

Table 5 shows the Pairwise Granger Causality Tests. Moreover, the logarithmic series of the proportion of employees in the secondary industry was the Granger causality of the logarithmic series of carbon dioxide emissions. It showed that all the series data passed the test and fulfilled the requirements of regression analysis.

**Table 5.** Pairwise Granger Causality Tests.

| Null Hypothesis | F-Statistic | Prob. | Conclusion |
|-----------------|-------------|-------|------------|
| \(\ln X_4\) does not Granger Cause \(\ln Y\) | 6.251     | 0.021 | reject     |
| \(\ln Y\) does not Granger Cause \(\ln X_4\) | 2.850     | 0.107 | accept     |

Table 6 shows the results of the correlation analysis. By testing the correlation coefficient between the independent variables, if the correlation coefficient between any two variables is close to 1 or \(-1\), it indicates that in the variables exists a serious multicollinearity problem. The correlation coefficient matrix was obtained by using the comprehensive statistical test method for the multicollinearity test. The results showed that in the variables, there existed multicollinearity.

**Table 6.** The correlation analysis.

| Variable | \(\ln X_1\) | \(\ln X_2\) | \(\ln X_3\) | \(\ln X_4\) |
|----------|-------------|-------------|-------------|-------------|
| \(\ln X_1\) | 1           |             |             |             |
| \(\ln X_2\) | 0.849       | 1           |             |             |
| \(\ln X_3\) | -0.963      | -0.731     | 1           |             |
| \(\ln X_4\) | 0.808       | 0.768       | -0.732     | 1           |
Table 7 shows the multicollinearity test result. This paper also used the variance expansion factor method to further test multicollinearity. It showed that the VIF values of lnX1 and lnX3 were greater than 10, which indicated that there was multicollinearity between the independent variables. Therefore, the least squares method (OLS) was not suitable for the unbiased estimation of the data series in this study.

Table 7. Multicollinearity test result.

| Variable | Coefficient Uncentered | Variances | VIF |
|----------|------------------------|-----------|-----|
| C        | 694.989                | 2,985,714.000 | NA |
| ln X1    | 5.817                  | 3,470,345.000 | 41.228 |
| ln X2    | 1.254                  | 98,031.080 | 5.857 |
| ln X3    | 0.157                  | 9134.534 | 22.920 |
| ln X4    | 0.053                  | 2423.158 | 3.190 |

In this paper, the ridge regression method was selected for simulation fitting, which eliminated the influence of multicollinearity to a certain extent. Although ridge regression analysis is a biased estimation method, it does not need to eliminate explanatory variables. It can ensure that the estimator has a small variance and does not make the sum of squares of residuals deviate too much from its minimum value, so as to obtain a more realistic and reliable regression process than the least square estimation [46]. The Ridge regression method is to add K (bias coefficient) to the main diagonal element of the independent variable standardization matrix so that the regression coefficient estimator can maintain a much greater accuracy than the unbiased estimator under the condition of small deviation, which can significantly improve the stability of the estimation [47]. The range of regression coefficient K was set between 0 and 1, and the data interval was 0.01. In this paper, SPSS software is used to analyze the data series and calculated the results in Figures 5 and 6. Figure 5 shows the ridge regression estimation on the model, and the ridge trace diagram. Figure 6 shows the scatter plot of the variation of the resolvable coefficient R² with the ridge regression coefficient K.

**Figure 5.** The ridge traces of the variables.
When $K = 0.130$, $R^2 = 0.978$, the regression coefficient of each variable tended to be stable. Table 8 shows the specific analysis results.

Table 8. Ridge regression result.

| Variable | Coefficient | Standard Error | Standard Coefficient | t-Statistic | Sig.t |
|----------|-------------|----------------|-----------------------|-------------|-------|
| $\ln X_1$ | 3.316       | 0.330          | 0.282                 | 10.056      | 0.000 |
| $\ln X_2$ | 2.468       | 0.568          | 0.171                 | 4.345       | 0.000 |
| $\ln X_3$ | $-0.667$    | 0.087          | $-0.257$              | $-7.674$    | 0.000 |
| $\ln X_4$ | 1.280       | 0.161          | 0.316                 | 7.966       | 0.000 |
| Constant | $-38.129$   | 4.022          | 0.000                 | $-9.481$    | 0.000 |

Note: $R = 0.988$ $R^2 = 0.978$ $F = 211.251$ Sig.(F) = 0.000.

The standard ridge regression equation was presented as follows:

$$\ln Y = 0.282 \ln X_1 + 0.171 \ln X_2 - 0.257 \ln X_3 + 0.316 \ln X_4$$

(5)

The corresponding ridge regression equation was presented as follows:

$$\ln Y = -38.129 + 3.316 \ln X_1 + 2.468 \ln X_2 - 0.667 \ln X_3 + 1.280 \ln X_4$$

(6)

It was showed that the F-statistic of ridge regression model was significant ($F = 211.251$, $P = 0.000$). All the explanatory variables passed the 1% significance level test, indicating that the overall fitting effect of the model was good.

The results showed that the population of China, the proportion of the working-age population, the Engel coefficient, and the proportion of employee population in the secondary industry all had significant effects on carbon dioxide emissions. According to the elasticity of the influencing factors, followed by population size (3.316), the proportion of the working-age population (2.468), the proportion of employees in the secondary industry (1.280), and the Engel coefficient ($-0.667$).

6. Discussion

From the results of ridge regression analysis, it could be seen that the changes in China’s population structure had a significant impact on carbon dioxide emissions.
terms of population size, the number of populations had a significant positive impact on carbon dioxide emissions, and the impact was the largest. Carbon dioxide emissions would increase by 3.316% for every 1% growth in population. Since 1995, with the continuous implementation of the family planning policy, the family planning work has achieved remarkable results that China’s fertility rate had gradually declined. However, China’s population was still rising because of the population structure, which took less and less proportion in the world population year by year. The increase in population has destroyed the ecological environment and changed the forms of land utilization, resulting in the squeeze of human living space. With the increasing demand for energy by a large number of people, the carbon dioxide generated by energy consumption was also gradually increasing. Therefore, the population is still the main driving factor of China’s carbon emissions. In the future, China’s population, resources, and environment are still under great pressure. Therefore, on the basis of implementing the national family planning policy, we should control the population and pay close attention to the impact of population change on carbon emissions.

The continuous increase in the proportion of the working-age population has provided a rich labor supply for China’s economic construction. While promoting economic growth, it has led to an increase in carbon emissions. The elastic coefficient of the proportion of the working-age population is 2.468, which confirms the clear correlation between the population age structure of China and the carbon emissions. Thus, the labor-aged population ratio is also another important indicator for promoting the growth of carbon emissions. The rapid decline in birth rate has led to the acceleration of the population aging, the rapid drop of child dependency ratio, and the rise of the working-age population. Then the demographic dividend formed during which the labor resources are abundant and the economy becomes more developed. The emergence of the demographic dividend has greatly promoted China’s economic development, accelerated the pace of urban construction, and promoted production and consumption. In the field of production, China is at a stage with abundant labor resources. With the implementation and improvement of China’s employment policy, the labor force participation rate and employment rate have maintained a high level, which has not only expanded the scale of production but also increased production efficiency. In the field of consumption, the residents of different ages have different consumption habits and consumption demands. The working-age population is in the period of consumption exuberance. The consumption growth will inevitably bring about an increase in energy use and carbon emissions. With the acceleration of China’s population aging process, the existing demographic dividend will gradually disappear, which will have an inhibitory effect on carbon emissions in production and consumption. Therefore, we should pay attention to improve the quality of the labor force population and optimize the population age structure.

At present, China is in the process of rapid development of industrialization and modernization. The secondary industry has become an important industry to promote China’s economic development. The proportion of the employed population in the secondary industry is increasing year by year and remains stable in a period of time. Thus, it forms an economic development mode with the secondary industry as the main driving force. The construction and automobile industries with high energy consumption and pollution account for a high proportion of the whole industrial system. So, they lead to an increase in energy consumption. China’s economic development is at the cost of excessive energy consumption. Therefore, on the premise of maintaining stable economic development, China should reduce the energy intensity and improve the energy utilization rate of industries emitting much carbon. We should reform the industrial structure of the industrial sector and reduce the proportion of heavy industry. Meanwhile, we also need to develop the high-tech industries and optimize the industrial structure. The government should promote the transformation from the secondary industry to the tertiary industry so that the economic development will transform from an industrial structure to a service-oriented industrial structure gradually. We should economize and make rational
use of resources, reducing the environmental pollution caused by the secondary industry, promoting the development of China’s low-carbon economy, and adhere to the road of sustainable development.

From the perspective of population consumption structure, for every 1% increase in Engel coefficient, carbon emissions will be decreased by 0.667%. The Engel coefficient represents the proportion of residents’ total food expenditure in total personal consumption expenditure. The lower the household income is, the more the expenditure on food accounts for the total household expenditure. As the household income increases, the proportion of food consumption in the total household expenditure will decrease. Therefore, the Engel coefficient is one of the main standards to measure the wealth of a family or a country, which indirectly reflects the level of the economy. There are two main factors that affect carbon emissions. One is the energy consumption of people living, another is the consumption of national economy industry meeting the customer demand to energy. The consumption of food decreased and the consumption level of other aspects increased, which directly promoted the carbon emission. From the changing trend of the Engel coefficient, the Engel coefficient shows a downward trend year by year. It shows that the growth of the social economy increases the income of residents. The increase of residents’ income promotes the consumption of residents, and consumption will drive the development of industry, finally leading to increase carbon emissions. Therefore, with the increase of income of residents, it is necessary to guide the residents to set up a correct consuming concept that people should develop a rational consumption habit. Meanwhile, it is necessary to prevent excessive consumption and avoid forming a large-scale high-carbon consumption mode. Also, it is significant for people to raise awareness on saving and environmental protection, so as to prepare for the construction of an environment-friendly society.

7. Conclusions, Limitation and Future Research

This paper studied the impact of population structure changes on carbon emissions in China and we drew the following conclusions.

First, population size had a significant impact on carbon emissions, and the impact degree was the largest. The coefficient of elasticity was 3.316. There also existed a long-term equilibrium relationship. Population size had a synergistic effect on carbon emissions. The more people there were, the more energy they consumed, and the more carbon dioxide were emitted.

Second, the population age structure, that is, the proportion of the working-age population (15–64 years old) had a significant impact on carbon emissions. The influence degree is second only to the population size factor, and the coefficient of elasticity was 2.468. As the proportion of the working-age population increased, carbon dioxide emissions also increased. And there was a positive relationship between them. Within a certain period of time, this relationship would remain stable for a long time.

Third, the population employment structure, that is, the proportion of employees in the secondary industry had a significant impact on carbon emissions. The influence degree on carbon emissions ranks third, with a coefficient of elasticity of 1.280. The greater the proportion of employees in the secondary industry was, the more the carbon dioxide was emitted, so there was a long-term stable relationship between them.

Forth, the population consumption structure was represented by the Engel coefficient. In the ridge regression model, the coefficient of this variable was −0.667, which had the smallest impact on carbon emissions. It indicated that the lower the coefficient was, the less the residents spent on food and the higher the consumption in other aspects and the more carbon dioxide was emitted. Therefore, there was a negative correlation between the Engel coefficient and carbon emissions.

There are still some limitations in this study. One is embodied in the deviation in the calculation of carbon dioxide emissions from the sample data. There are many ways to emit carbon dioxide, like combustion of fossil energy, some physical and chemical reactions set off from producing the cement, lime, calcium carbide, steel, etc. However, in all the
carbon dioxide emitted by the industrial production process, cement accounted for 56.8%, lime accounted for 33.7%, calcium carbide and steel production accounted for less than 10% [44,45]. Lime, calcium carbide, and steel were not counted in this paper, because their emissions were so few that it was difficult to get the data. In future research, improving the population structure and formulating more effective carbon emission reduction strategies are still the main contents.

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