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IMPACTS OF DEMOGRAPHIC FACTORS ON CARBON EMISSIONS BASED ON THE STIRPAT MODEL AND THE PLS METHOD: A CASE STUDY OF SHANGHAI

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Abstract

The heavy dependence on fossil-based energy and inefficient use of energy add to the relentless growth of carbon emissions in China, and also lead to an array of serious environmental pollution issues, such as haze and smog. This situation threatens the health of residents and the sustainable development of society. China has to face the huge pressure of carbon emissions from international and domestic societies. This study aims to investigate the demographic driving factors of carbon emission in Shanghai from 1996 to 2015. The Stochastic Impacts by Regression on Population, Affluence and Technology model (STIRPAT) and partial least squares (PLS) regression method are used. Results show several key findings. (1) Population age structure, occupation and education are significant driving forces for carbon emission. (2) Educational structure and population size positively and statistically significantly affect carbon emissions with elastic coefficients of 0.017 and 0.011, respectively. However, age, occupational and gender structures and population density have constraining effects. (3) Environmental regulation has achieved initial success in reducing carbon emissions, and its negative coefficient (-0.181) supports the Porter hypothesis. The effects of GDP per capita and energy intensity on carbon emissions are positive with elastic coefficients of 0.004 and 0.013, respectively. These findings contribute to a complete theoretical framework of the effects of demographic factors on carbon emissions. Concrete and viable policy recommendations are provided to improve urban emission abatement and progress of the low-carbon city.

Key words: carbon emission, demographic factors, PLS regression, STIRPAT model

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1. Introduction

Greenhouse gas emissions have attracted attention worldwide because of the worsening global warming and ecosystem degradation (Wei et al., 2019). Given that CO_2 is one of the most important greenhouse gases, various countries share a common mission to promote carbon emission abatement and attain low-carbon economy. The rapid progress of industrialization, urbanization and modernization has led to the continuous and remarkable increase in energy consumption and carbon emission in China. Fig. 1 shows the trend of the changes in total carbon emissions amongst China and major developed countries from 1996 to 2014. The Figure shows that the carbon emissions in Germany, US, UK and Japan are stable and follow a steady downward trend. However, those of China increased sharply from 3,463,089 kt in 1996 to 10,291,927 kt in 2014, thereby reflecting an increase of 197.19%.

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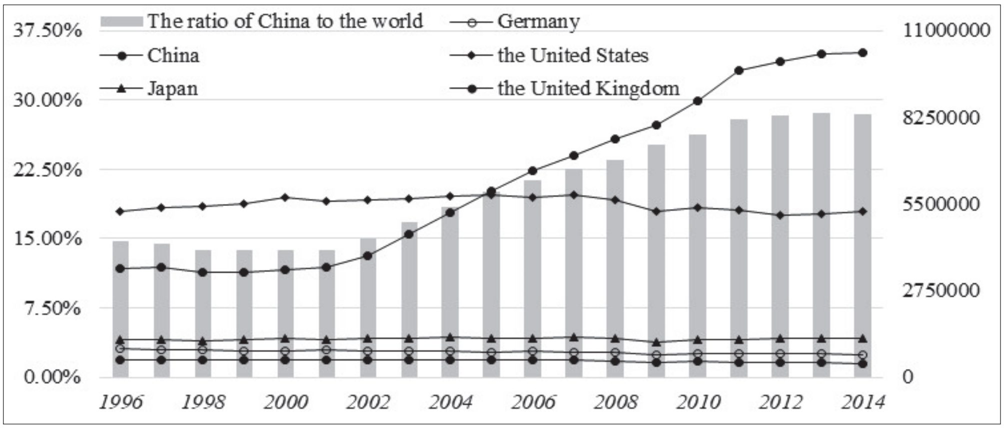

Fig. 1. Trends of total carbon emissions in the world major countries from 1996 to 2014 (World Bank database, 2017)
Note: The ratio of China to the world refers to the share of carbon emissions in China in the world (Refer to the left axis: %). Total carbon emissions in China, Japan, Germany, the United States and the United Kingdom (Refer to the right axis: 1,000 tons).

China's carbon emissions in 2014 accounted for 28.48% of the world total emissions, thereby making this country the world's largest emitter. China has made several important commitments on emission reduction at international conferences, and has promised to reduce its carbon intensity by 40%-45% from 2005 to 2020 and reach the peak of carbon emissions by 2030. However, this emission reduction target appears challenging because China faces enormous pressure to balance economic growth and emission abatement. Therefore, the key contributing factors of carbon emissions must be identified to ensure the achievement of the policy targets.

Some influential reports, such as the Fourth Assessment Report (AR4) from the Intergovernmental Panel on Climate Change (IPCC, 2007) and State of World Population 2009, indicated that the changes in demographic factors are recognized as the major causes of high carbon emissions and have recently become major topics on carbon emissions. In China, household energy carbon emissions have become the second largest source of carbon emissions after the industrial sector. However, the majority of the related studies have only investigated the effects of population size on carbon emissions, and concluded that population size is the main factor influencing the increment of carbon emission (Guo and Sun, 2017; York et al., 2002). In addition, a burgeoning body of literature has explored the effects of other demographic driving factors on carbon emission. These factors include population density (Chai, 2013; Liddle, 2014), age structure (Sun, 2018; Chen, 2018), gender structure (Li and Zhou, 2019), educational structure (Li and Zhou, 2019) and occupational structure (Li and Zhou, 2019).China is in a critical stage of social transformation, and the population factor is undergoing tremendous changes. The population growth rate is slowing down, but the population base is massive. The population structure is facing major challenges. The urbanization level is surging, the aging process is accelerating, and the family size is decreasing. These changes will affect carbon emissions by influencing production and consumption patterns. Therefore, the introduction of population structure into the framework of carbon emission analysis can reveal the particular population problems underlying the carbon emissions in China, and serve as a substantive decision-making reference for emission abatement.

Urban areas are the main source of carbon emissions. The development of cities indicates an increase in the proportion of urban population and also involves changes in industrial structure and consumer market, amongst others (Wei et al., 2018). This research studies urban carbon emissions, which is significant for governments to formulate emission reduction policies. Shanghai is an international metropolis and has experienced rapid economic and population growth. The total population of Shanghai increased significantly from 14.51 million in 1996 to 24.15 million in 2015 (SMBS, 2016). The population density maintained an upward trend, increasing from 2288 persons/km^2 in 1996 to 3809 persons/km^2 in 2015 (SMBS, 2016), thereby representing an increase of 66.48%. The changes in the population structure of Shanghai are inevitable. The proportion of people aged 65 years old and above was 12.82% in 2015 (NBSC, 2016a), thereby indicating that Shanghai is accelerating towards an aging society. The gender ratio of men and women was unbalanced and continuously declined from 101.75% in 1996 to 98.59% in 2015 (SMBS, 2016). In terms of educational level, the proportion of people with college degree or above increased remarkably from 10.3% in 1996 to 27.13% in 2015 (MEPRC, 2016). The occupational structure evolves towards a 'denationalization' trend. The share of employees in state-owned organizations in the urban areas decreased sharply from 61.1% in 1996 to 8.4% in 2015 (NBSC, 2016b), thereby representing a decreasing trend. In addition, Shanghai is a major player in carbon reduction policies (Zhang et al., 2012). This city has implemented the light vehicle national six-b emission standards, thereby showing the determination to curb carbon emissions. These changes in population size and other demographic factors may have profound effects on the mode of production and consumption structure, and ultimately change Shanghai's trajectory of carbon emissions.

This study applied the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model to analyze the driving factors of carbon emission. In recent years, numerous studies have discussed the driving forces of energy-related carbon emissions and achieved substantial valuable insights. Many different methods have been developed to examine the influencing mechanisms of anthropogenic factors. Particularly, the STIRPAT model is one of the most widely applied approaches to address such issues (Li et al., 2015). Population, economy and technology are considered important factors in determining carbon emissions, and they form a comprehensive system for the conduct of research on carbon emissions.

This study aims to investigate the influence of demographic factors on carbon emissions and identify the main driving factors at urban levels. Shanghai is selected as the research case because of its status as the largest economy and major emitter in China. Several specific questions are investigated: (1) What are the key demographic parameters affecting carbon emission in Shanghai? (2) What are the directions of the effect and the magnitudes of each variable? (3) What are the influencing mechanisms of the demographic factors on carbon emissions? This time-series analysis uses the STIRPAT model to investigate the influence of demographic factors on carbon emission by breaking down the population factors into specific parameters from 1996 to 2015. Given that the STIRPAT model is sensitive to collinearity problems, the partial least squares (PLS) method is used to accurately determine the influencing direction and magnitude of each variable.

The main contributions of this study are as follows. (1) By expanding the STIRPAT model and disaggregating demographic factors, this study contributes to a complete and tenable theoretical framework for investigating the demographic influences on carbon emissions. (2) By integrating the STIRPAT framework with the PLS models, this research provides a practical approach to quantify the influence of the demographic factors on urban carbon emissions. (3) The research findings provide a reliable and operational reference for policy makers. The central and local governments can develop complete and responsive strategies and action plans for carbon emission abatement on the basis of the demographic features.

2. Previous studies

Many studies have focused on the driving factors of carbon emissions. A consensus that economic development, technological level and population size are the primary drivers of carbon emission changes has been reached. York et al. (2002) argued that wealth, technology and population have varying effects on carbon emissions.

Wang et al. (2005) used the logarithmic mean Divisia index method to confirm the critical role of technology in reducing carbon emissions. Lantz and Feng (2006) performed regression analysis and found that population and technology are the main determining factors of carbon emission change. Ding et al. (2012) studied the effects of wealth, technology and population on carbon emissions in industrial sectors. The results showed that wealth and population are the main contributors for the growth of carbon emissions, whilst technology has a constricting effect. Shahbaz et al. (2015) concluded that wealth and urbanization contribute to the increase in energy consumption in Malaysia. Tang et al. (2017) analyzed the influencing factors on carbon emissions of residents and found that population size, energy structure and energy intensity directly affect carbon emissions.

The strand of studies focusing on the influence of population on carbon emissions can be sorted in four research domains: (1) relationship between population size and carbon emissions, (2) the influence of urbanization on carbon emissions, (3) role of age structure on carbon emissions and (4) contribution of household size to carbon emissions.

Firstly, population size is a critical factor in carbon emissions. The related studies have mainly focused on three issues: causal relationship, working mechanism and magnitude of influence. Birdsall (1992) concluded that population growth affects carbon emissions mainly through two channels, namely, increase in energy consumption and changes in land uses. Knapp and Mookerjee (1996) used Granger's test and revealed the causal link between population growth and carbon emission growth. Shi (2003) used the data from 93 countries (i.e., 26 low-income, 24 low middle-income, 14 upper middle-income and 29 high-income countries) from 1975 to 1996 and found that the elasticity coefficient of carbon emissions to the total population is 1.42. Huang et al. (2016) used the STIRPAT model as basis to conclude that a 1% change in population coincides with a 3.467% change in carbon emissions in Jiangsu Province, China. Table 1 shows the details of the preceding studies. Secondly, urbanization is another important demographic factor.

The rapid and widespread urbanization in China has led to serious environmental issues (Wei et al., 2015a; Wei et al., 2015b). Many studies have traditionally selected urbanization as the primary influencing factor of carbon emissions. Jones (1989) used the regression analysis of 59 developing countries as basis to conclude that urbanization is a significant factor in post-industrial energy consumption. Liu (2009) used the autoregressive distributed lag and factor decomposition model and determined a stable long-term relationship between urbanization and energy consumption. Zhang et al. (2014) utilized the STIRPAT model in analyzing the determinants of carbon emissions from energy consumption in Anhui Province.

Table 1. The details of literatures about population size and carbon emissions

Author(s) and Year	***Variables***	***Methodology***	***Results***	***The effect of population size***
Knapp and Mookerjee (1996)	CO_2; Population.	Granger causality test; Error correction and cointegration models.	The results suggest there is a short-term dynamic relationship between CO_2 and population.	+
Shi (2003)	Carbon dioxide emissions; GDP per capital; Population; Value added of manufacturing sector to national GDP; Value added of services sector to national GDP; Percent of working-age population.	STIRPAT model; GLS	The increase of global population over the last two decades is proportional to the growth of carbon dioxide emissions. The impact of increasing population on emissions is much more pronounced in developing countries than in developed countries.	+
Huang et al. (2016)	Carbon consumption; Population; Per capita GDP; Energy intensity; Urbanization level in Jiangsu Province.	STIRPAT model; Ridge regression	For every 1% change in population, per capita GDP, energy intensity, and urbanization level, the carbon emissions in Jiangsu Province will increase by 3.467%, (0.242+0.024lnA)%, 0.313%, and 0.151%, respectively.	+

The results indicated that urbanization significantly and positively affects carbon emissions. Li et al. (2015) studied the influencing factors of carbon emission in Tianjin, China between 1996 and 2012. The estimation results revealed that urbanization is a considerable contributing factor. Table 2 illustrates the details of the preceding studies.

Thirdly, the study of the relationship between population age structure and carbon emissions mainly focuses on the effect of population aging. However, people of different ages have varying consumption willingness and spending power, thereby indirectly resulting in various production and consumption patterns**.** Menzand Kühling (2011), and Menz and **Welsch** (2012) considered that carbon emission increases with an increasing significant proportion of aging adults. Fan et al. (2006) analyzed the carbon emissions of 64 countries with different income levels from 1975 to 2000.The proportion of people aged 15-64 years old was positively related to the carbon emissions from low-income countries and has a restraining effect on high-income ones. Dalton et al. (2008) compared the role of population aging and technology in reducing the US' carbon emissions, and found that population aging in some cases could produce better effects than technological advancement. Dalton et al. (2008), Li et al. (2011) and Tian et al. (2015) showed that population aging could serve as a reference for carbon reduction policies. Table 3 presents the details of the above-mentioned studies. The effects of household size on carbon emissions have also drawn substantial academic attention. Dalton et al. (2007) and Jing et al. (2008) found that the introduction of household size could enhance the explanatory power of the carbon emission model. Druckman and Jackson (2016) investigated the effects of household size on carbon emission. The empirical results showed that a small-size household is a driving factor for increased carbon emissions. Ma et al. (2013) advocated the use of dynamic models to investigate the determinants of carbon emissions. The results revealed that household size generates inhibitory effects on carbon emissions. Yang et al. (2015) explored the effects of population on carbon emissions in Beijing, and concluded that household size could have an adverse effect. Additionally, population densities have been considered in the study of carbon emissions.

Chai (2013) studied the influencing factors of carbon emissions per capita in 30 capital cities in China, and concluded that population density could affect the 'carbon emission' of residents. Liddle (2004, 2014) found that population density reduces energy consumption and carbon emissions. Table 4 shows the details of the preceding studies. The present literature is limited in several aspects. Firstly, the existing studies on the effects of population structure on urban carbon emission have mainly involved limited factors, such as the urban–rural population structure, age structure and household size, but disregarded several important ones, including gender, education and occupation. Secondly, the existing research has mainly focused on the national or provincial level with insufficient consideration of the demographic factors at the municipal level. China is currently at the stage of rapid urbanization (Wei et al., 2016). NSBC (1997-2016) reported that over half of China's population currently live in cities.

Table 2. The details of literatures about urbanization level and carbon emissions

Author(s) and Year	***Variables***	***Methodology***	***Results***	***The effect of urbanization***
Liu （2009）	Energy consumption; Population; GDP; Urbanization rate	Autoregressive Distributed Lag (ARDL) testing approach; Factor decomposition model.	The driving effect of urbanization on energy consumption is declining.	+
Zhang et al. (2014)	Total carbon emissions; Secondary industry output value; Tertiary industry output value; Urbanization rate; Urban built-up area; Per capita disposable income of urban residents; Energy intensity.	STIRPAT model.	During 2000-2011, the total carbon emissions will increase by 1.2088%, 0.2020%, 0.5023%, 4.7938% and 1.0660% for every 1% increase in the output value of the secondary industry, the output value of the tertiary industry, the proportion of urban population, the urban built-up area, and the per capita disposable income of urban residents.	+
Li et al. （2015）	CO_2 emission; Population size; Urbanization level; Affluence level; Energy intensity; Industrialization level; Foreign direct investment.	STIRPAT model; PLS.	The rapid process of urbanization has the greatest impact on the increase in carbon emissions, while the industrialization rate has the least impact.	+

Table 3. The details of literatures about population age structure and carbon emissions

Author(s) and Year	***Variables***	***Methodology***	***Results***	***The effect of population aging***
Fan et al. （2006）	CO_2 emissions; GDP per capita; Population; Technology; Urbanization; Population aged between 15–64.	STIRPAT model	The population aged between 15- and 64-year-old has a negative impact on the total CO_2 emissions of countries at the high income level, but the impact is positive at other income levels.	+ (countries at the high-income level) - (countries at the low income level)
Dalton et al. (2008)	CO_2 emissions; Aging population; Technical change.	Population-environment-technology (PET) model	Aging population has taken a constraining effect on long-term emissions, by almost 40% in a low population scenario, and such effects of aging population on emissions can be as large, or larger than the effects of technical progress.	-
Menzand Kühling (2011)	Carbon emissions; Population size; Income per capita; Urbanization.	STIRPAT model	The evolutionary trends in both the age and the cohort composition of the population have significantly contributed to increasing carbon emissions in OECD countries.	+
Li et al. (2011)	Carbon emissions; Total population; Urbanization rate; Aging rate; Engel coefficient; Secondary industry population accounts for the employed population.	STIRPAT model	The aging population has a negative effect on carbon dioxide emissions, and the acceleration of population aging has a negative effect on long-term carbon emissions.	-
Tian et al. (2015)	Carbon emissions; Population age structure; Urbanization rate	STIRPAT model	China's population of different ages has taken different effects on carbon emissions. Among them, the population aged 30 to 44 has the greatest impact on increasing carbon emissions, the impact of the population aged 15 to 29 is not significant, and the proportion of population aged 60 and over has a negative impact on carbon emissions.	-

Given the rapid economic development in cities, particularly in Shanghai, and the continuous change in population structure, cities overtaking rural areas have become major contributors to carbon emissions. Consequently, the current study investigates the effects of population on carbon emissions in Shanghai to fill in this knowledge gap. Several demographic factors are incorporated in the empirical estimation.

3. Material and methods

3.1. Data sources

This research conducted time-series analysis from 1996 to 2015. The per capita carbon emission index is taken from the *China Energy Statistical Yearbook*. The population size, population density, child dependency coefficient, elderly dependency coefficient, population gender structure, population educational structural data and urbanisation level are taken from the *Shanghai Statistical Yearbook* and *China Statistical Yearbook*. The population occupational structural data are obtained from the *China Labor Statistical Yearbook*. The raw data of GDP per capita are sourced from the *China Statistical Yearbook*. The GDP per capita is deflated at the 1996 level to eliminate price fluctuation. The energy consumption intensity is sourced from the *China Energy Statistical Yearbook*. The environmental regulation data are sourced from the *China Environmental Statistical Yearbook*.

3. 2. STIRPAT model

IPAT is a classic model and widely used to analyse the influencing factors of environmental changes owing to its ease of use. This model considers the influence of population (*P*), assets (*A*) and technology (*T*) on the environmental change (*I*). However, this model can only reflect the same proportional effects of various factors on environmental pressure, which is inconsistent with reality. To overcome the limitations of IPAT, Dietz and Rosa (1997) proposed a stochastic environmental impact model based on the IPAT model, namely, the STIRPAT model (Eq. 1):

$$I_{it} = a \times P_{it}^{b} \times A_{it}^{c} \times T_{it}^{d} \times e_{it} \tag{1}$$

where: *i* refers to the economic entity; *t* denotes the time; *I* is the environmental pressure, such as CO_2 emissions; *P* denotes the population factors; *A* is wealth; *T* refers to the technical efficiency, which is often reflected by the energy consumption intensity; *e* is the random error; *a* is the constant terms and *b*, *c* and *d* are the coefficients.

The STIRPAT model is a mainstream method used to quantitatively analyze the influence of demographic factors on the environment. This model is often transformed logarithmically to evaluate the contribution of each factor and effectively control the heteroscedasticity of the model, which is shown as the following linear model (Eq. 2):

$$\ln I_{it} = a + b \times \ln P_{it} + c \times \ln A_{it} + d \times \ln T_{it} + e_{it} \tag{2}$$

where: *b*, *c* and *d* denote the coefficients of elasticity between environmental pressure and population, wealth and technology, respectively. The equation indicates that *b*%, *c*% and *d*% of the environmental changes are achieved when the population, wealth and technology, respectively, change by 1%.

Note that STIRPAT is a flexible method that is used to examine multiple influencing factors on the environment by decomposing the factors in the population, affluence and technological aspects. This research extends the model specifications (Eq. (3)) by including a wide array of demographic factors and breaking down the technology factor into the variables of 'energy intensity' and 'environmental regulation' to comprehensively analyze the effect of demographic factors on carbon emissions. Urbanization rate is also included in the model. The expanded model is expressed as follows (Eq. 3):

$$\begin{aligned} \ln PCCE_{it} &= a + b_s \times \ln PSIZE_{it} + b_t \times \ln PT_{it} + c \times \ln PDGP_{it} + \\ &+ d_e \times \ln ECI_{it} + d_p \times \ln ER_{it} + d_u \times \ln URB_{it} + e_{it} \end{aligned} \tag{3}$$

where: *PCCE* is the carbon emission per capita, *PSIZE* is the population size, *PT* is the population structure, *PGDP* is the GDP per capita, *ECI* is the intensity of energy consumption, *ER* is the environmental regulation, and URB is the urbanisation rate. This study further decomposes the factor of population structure into 'population density', 'age structure', 'gender structure', 'educational structure' and 'occupational structure

Age structure can be further divided into the child and elderly dependency ratios, which are provided as follows (Eq. 4):

$$\begin{aligned} \ln PCCE_{it} &= a + b_s \times \ln PSIZE_{it} + b_{tf} \times \ln PD_{it} + b_{tu} \times \ln GS_i + \\ &+ b_{ty} \times \ln CDR_i + b_{to} \times \ln EDR_i + b_{th} \times b_{th} \times \ln ES_i + \\ &+ b_{ts} \times \ln OS_i + c \times \ln PGDP_{it} + d_e \times \ln ECI_{it} + d_p \times \\ &\times \ln ER_{it} + d_u \times \ln URB_{it} + e_{it} \end{aligned} \tag{4}$$

where: *PD*, *GS*, *ES* and *OS* denote the population density, gender structure, population educational structure and occupational structure, respectively; and *CDR* and *EDR* refer to the child and elderly dependency ratios, respectively.

These two variables measure the age structure of the population. Table 5 shows the specific definition of variables. Note that the STIRPAT model disregards the multicollinearity between independent variables when analyzing the effects of population, wealth, technology and other factors on environmental changes.

Table 4. The details of literatures about household size and carbon emissions

Author(s) and Year	***Variables***	***Methodology***	***Results***	***The effect of household size***
Druckman and Jackson (2016)	Total carbon emissions; Total households; Average household size; Per capita household consumption; Energy intensity.	STIRPAT model	The total number of households has a positive effect on the increase in carbon emissions, while household size has a negative effect on the increase in carbon emissions.	-
Ma et al. (2013)	CO_2 emissions; Population size; Age structure; Family size; Urbanization rate	STIRPAT model	Population size, urbanization rate and age structure are the main demographic factors driving China's CO_2 emissions, while large household size has a constraint effect on China's CO_2 emissions.	-
Yang et al. (2015)	Per capita carbon emissions; Population structure; Household size; Urbanization.	STIRPAT model	The trend of smaller household size and expansions of floating population boost the discharge of carbon emissions.	-

Table 5. Variable description

Variable	***Abb***	***Definition***	***Units***
Per Capita Carbon Emission	PCCE	The ratio of the total carbon emissions to the total population	10^4 tons/Person
Population Size	PSIZE	Gross population	10 thousand people
Population Density	PD	The ratio of total population to land area	Person/square kilometer
Child Dependency Ratio	CDR	The ratio of the population aging from 0 to 14 to between 15 and 64 years	%
Elderly Dependency Ratio	EDR	The ratio of the population aged 65 and over to the population aged 15–64 years	%
Gender Structure of Population	GS	The ratio of men to women	%
Population Education Structure	ES	The proportion of people with college degree or above	%
Population Occupation Structure	OS	The share of employees in state-owned units in the urban employment	%
Per Capita GDP	PGDP	The ratio of GDP to total population	Yuan, deflated price (taking 1996 as the baseline level)
Energy Consumption Intensity	ECI	Coal consumption/GDP	Ton standard coal/million
Environmental Regulation	ER	Environmental protection investment/GDP	%
Urbanization Level	URB	the proportion of non-agricultural population in the total population	%

Therefore, further investigation should be conducted after using STIRPAT to establish an analytical model. For multicollinearity problems, the PLS method is generally used for regression analysis.

3.3. PLS regression

PLS regression is an effective method to overcome the multicollinearity existing in the STIRPAT model. This method combines the advantages of principal component analysis, canonical correlation analysis and multivariate linear regression. The use of information synthesis and screening techniques will enable the PLS regression to extract the principal components from the independent variable system. The underlying rationales of this method are introduced as follows.

Firstly, the principal components t_1 and μ_1 are extracted from the independent and dependent variable systems, respectively. However, t_1 and μ_1 must satisfy the principle of representation and relativity. That is, t_1 and μ_1 can disclose information on each variable system mutation, and t_1 can considerably explain μ_1.

Secondly, the regression of each variable to t_1 and that of every dependent variable to t_1 are performed after t_1 and μ_1 are extracted. If the accuracy requirement is reached, then the algorithm is terminated. Otherwise, the second principal component is extracted from the residual information of the independent and dependent variables, cycling back and forth until a satisfactory accuracy level is reached.

The mathematical model is shown as follows Eqs. (5-6):

$$X = TP^{'} + E \tag{5}$$

$$Y = UQ^{'} + F \tag{6}$$

The elements in the matrix of *T* and *U* represent the values of the independent variable system *X* and the dependent variable system *Y*, respectively. The elements of the matrix of *P* and *Q* are the loading matrices of *X* and Y, respectively. Variables *E* and *F* use the PLS method to fit the *X* and *Y* errors, respectively. Note that the PLS method also has limitations. This method is a linear analytical method that cannot fully express the nonlinear relationship amongst data. Therefore, the prediction accuracy of nonlinear data is low, and other methods should be sought.

4. Results and discussion

4.1. Model estimation

When the STIRPAT model is used to analyse the effects of population factors on carbon emissions in Shanghai, the stationarity of the related variables should be tested to ensure the accuracy of the regression results.

1) Smoothness test

The Augmented Dickey–Fuller Test (ADF) is a widely used method to test the stationarity of time-series data. If a time series becomes smooth after d-order differencing, then the original sequence is integrated of order *d*, which is *I(d)*. Table 6 presents the test results. Moreover, Table 6 shows that *lnPSIZE*, *lnPD*, *lnCDR*, *lnGS*, *lnOS*, *lnA*, *lnECI* and *lnER* are all stationary sequences. *lnI*, *lnEDR* and *lnES* are integrated of order 1, and further cointegration analysis is required.

2) Cointegration test

The Johansen cointegration test has better performance than the EG cointegration test for the test of cointegration relationship between multivariate variables: all the possible cointegration relationships can be presented without considering endogenous and exogenous variables, and the test results are more stable. Therefore, the current research uses Johansen's method as basis in analyzing the cointegration relationship amongst *lnl*, *lnEDR* and *lnES*. Table 7 shows that the trace-free statistics and maximum eigenvalue test demonstrate a cointegration equation between long-term population aging and long-term equilibrium population educational structure at the 5% significance level. Accordingly, all series are tested, and the regression models can be constructed to study the effects of carbon emissions.

3) Least squares regression

Given the possible correlation amongst the economic variables, the random error term may violate the assumption of no autocorrelation, thereby possibly resulting in inconsistent ordinary least squares (OLS) parameter estimates and inaccurate prediction results. Therefore, the autocorrelation test is beneficial in ensuring the validity of the regression analysis. Durbin-Watson (DW) is a commonly used method of the autocorrelation test, and the sequence autocorrelation is determined by the DW statistics. However, the process is completely dependent on the distribution of the DW statistics and the upper and lower limits of the critical values, which are only related to the sample size and number of explanatory variables. The specific values of the explanatory variables have no effects on the critical values, thereby inevitably affecting the accuracy of the test results. The Lagrange multiplier (LM) principle tests the autocorrelation of sequences to overcome the defects of DW. Therefore, the LM test of the residual sequence after the OLS regression is performed in this research. Table 8 shows the analytical results. The P value of the LM test result is 0.223, thereby indicating the absence of the sequence autocorrelation problem.

Multicollinearity is the main problem in the application of the STIRPAT model and may lead to inaccurate regression prediction. Therefore, this study examines the multicollinearity between independent variables by calculating the variance inflation factor (VIF) values. The multicollinearity amongst variables is generally accepted to be statistically significant when the VIF value is above 10. The last column of Table 8 shows that the VIF values of the majority of the variables are above 10, thereby indicating severe multicollinearity. To address the multicollinearity issue, this research uses the ridge and PLS regressions to analyze the aforementioned model.

4) Ridge regression

Ridge regression is a biased estimation method specifically used for collinear data analysis. This method is an improved least square, and the regression results are considerably reliable. The current study derives the following ridge map (Fig. 2) and trend graph of the coefficient of determination (Fig. 3).The K value is 0.08 and the coefficient of determination is 0.580. The ridge regression estimation results and variance analysis shown in Tables 9 -10, respectively, are obtained according to the K value. The F value is 2.998 and the P value is 0.046, thereby indicating that the model passes the statistical significance test. The corresponding ridge regression equation is given by Eq. (7), which shows that the most significant impact on carbon emissions between 1996 and 2015 in Shanghai is the gender structure of the population, and the coefficient is positive. This finding indicates that carbon emissions will increase by 3.150% for every 1% increase in the male-to-female gender ratio.

Moreover, the population age structure is analysed. The elasticity coefficients of the child and the old-age dependency parameters are -0.148 and -0.055, respectively. The elastic coefficients of the occupational and educational structures of the population are 0.036 and 0.023, respectively.

The elasticity coefficient of environmental regulation is -0.050.

$$\ln I = 3.150\ln PTS - 0.148\ln PTY - 0.055\ln PTO + 0.036\ln PTSOE + 0.023\ln PTC - 0.050\ln TP + 1.387 \quad (7)$$

Table 6. Unit root test results of each variable

Variable	*Differential order*	*t-statistics*	*Significance level*	*Threshold*	*Conclusion*
lnPCCE	1	−5.46	1%	−3.86	I(1)
lnPSIZE	0	−3.70	5%	−3.07	I(0)
lnPD	0	−3.69	5%	−3.07	I(0)
lnCDR	0	−2.16	5%	−1.96	I(0)
lnEDR	1	−4.73	1%	−3.86	I(1)
lnGS	0	−4.10	5%	−3.71	I(0)
lnES	1	−5.50	1%	−3.86	I(1)
lnOS	0	−1.75	10%	−1.61	I(0)
lnPGDP	0	−2.86	10%	−2.66	I(0)
lnECI	0	−7.36	1%	−4.67	I(0)
lnER	0	−3.38	5%	−3.03	I(0)
lnURB	0	-3.46	5%	-3.07	I(0)

Table 7. Results of Johansen cointegration

Cointegration hypothesis	*Eigenvalues*	*Trace Statistics*	*Threshold (5%)*	*P-value*	*Max-eigen statistic*	*Threshold (5%)*	*P value*
None*	0.782	39.410	24.276	0.0003	27.391	17.797	0.0013
At most 1	0.363	12.019	12.321	0.0561	8.130	11.225	0.1662
At most 2	0.194	3.889	4.130	0.0577	3.889	4.130	0.0577

** Means significant at the 5% level.*

Table 8. Least squares estimation results

Variables	*Coefficient*	*Standard error*	*t-statistics*	*P value*	*VIF*
C	17.424	12.887	1.352	0.213	
lnPSIZE	47.047	23.335	2.016	0.078	3256023
lnPD	−46.405	35.586	−1.304	0.229	3272900
lnCDR	−0.176	0.089	−0.649	0.083	50.535
lnEDR	0.085	0.137	−0.623	0.551	7.204
lnGS	−7.434	3.793	−1.987	0.086	276.338
lnES	0.209	0.408	0.513	0.621	239.428
lnOS	−0.038	0.089	−0.430	0.678	30.733
lnPGDP	0.986	1.032	0.955	0.368	5.934
lnECI	0.215	0.112	1.920	0.091	319.168
lnER	−0.075	0.280	−0.267	0.796	4.440
lnURB	0.429	1.081	0.397	0.702	100.94
R^2	0.953		**Adjust R^2**	0.869	
F-statistics	16.307		**DW**	2.125	
P value (F-statistic)	0.000				
LM test	1.486(0.223)				

Table 9. The estimation of ridge regression

Variables	*Coefficient without standardization*	*Standard Error*	*Coefficient after standardization*	*T-value*
lnPTS	3.150	1.208	0.676	2.608
lnPTY	-0.148	0.047	-0.753	-3.160
lnPTO	-0.055	0.049	-0.226	-1.126
lnPTSOE	0.036	0.022	0.403	1.645
lnPTC	0.023	0.030	0.158	0.769
lnTP	-0.050	0.165	-0.067	-0.304
Constant	1.387	0.302	0.000	4.597

Table 10. The variance analysis of ridge regression

	df	*SS*	*MS*	*F-value*	*Sig F*
Regress	6.000	0.032	0.005	2.998	0.046
Residual	13.000	0.023	0.002		

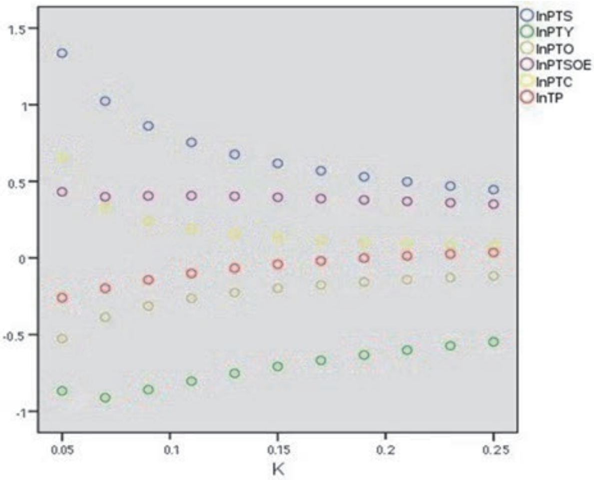

Fig. 2. Ridge trace

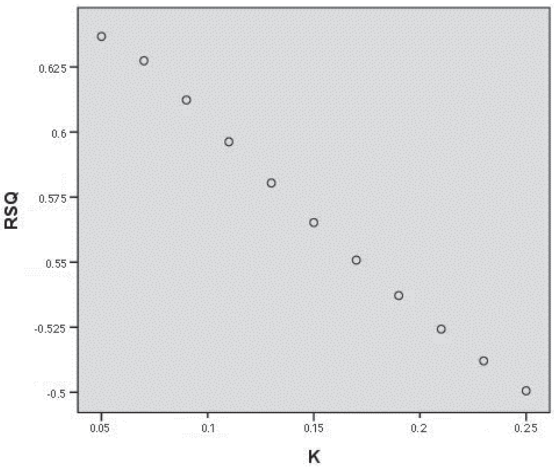

Fig. 3. The trend of coefficient of determination

The accuracy of the regression results needs to be further studied because the ridge regression determines the ridge parameters by subjective inspection. Additionally, the effective variables are difficult to filter. Therefore, the ridge regression is only a preliminary discussion on the STIRPAT model. This research mainly uses the PLS regression to estimate the impact of Shanghai's population factors on carbon emissions. The empirical results provide policy recommendations for the development of low-carbon economy in Shanghai.

5) PLS regression

This study performs PLS regression for the STIRPAT model, and Table 11 shows the results. Prior to the analysis of the specific effects of each contributing factor, the fitting effects of the model should be firstly explained. Firstly, the suitability of the PLS regression model for the data sample was tested with reference to the $t_1 = t_2$ oval plot and $t_1 = u_1$ scatter plot. Figs. 4 -5 show the testing results on the applicability of the PLS method. When the sample points are in the elliptical region (Fig. 4), no specific point is noted, and the model fitting effect is good. Evidently, all samples in this research can be accepted. Fig. 5 reflects the approximate relationship between the independent and dependent variables. An approximately linear pattern shows that the model is acceptable, and the PLS analysis is feasible.

Table 11 shows that R2Y (cum) is 0.931, and Q2 (cum) is 0.804, thereby indicating that the explanatory power of the model on the dependent variable is as high as 93.1% and has a prediction capability of 80.4%. The precision is high and the estimation result is reliable. The regression coefficients of the independent variables show that population size, educational structure, GDP per capita and energy consumption intensity have positive effects on carbon emissions. By contrast, the child dependency parameter, old age dependency parameter, occupational structure, population density, gender structure of population and environmental regulation on carbon emissions have negative effects.

VIP measures the marginal contribution of the independent variable to the principal component. Evidently, VIP is a quantitative index reflecting the importance of independent variables in explaining the dependent variables (Fan et al., 2006). Fig. 6 and Table 12 show that the most important factors affecting carbon emission are child support factor, environmental regulation, GDP per capita, old dependency coefficient, population occupational structure, population educational structure, energy consumption intensity, population gender structure, population density and population size.

Yang et al. (2015) explained that a VIP above 0.8 indicates that the independent variable has a strong explanatory power over the dependent variable. The estimation results indicated that the majority of the variables have significant effects on carbon emissions.

4.2. Result discussions

The child and elderly dependency ratios exert negative effects on carbon emissions. The findings reflect the strong parenting and pension pressures of the working population of Shanghai. The coefficients of elasticity of the two ratios are -0.088 and -0.021, respectively. This finding indicates that when the child and old age dependency ratios decrease by 1%, the carbon emission in Shanghai will increase by 0.088% and 0.021%, respectively. The life cycle hypothesis provides that the working age populations allocate their income on savings to meet the growth and retirement needs of the next generation.

When the labour population has low parenting and pension pressure, household consumption rate, demand for energy-intensive products and carbon emissions will increase. Fig. 7 shows that the child and old age dependency ratios in Shanghai steadily declined from 1996 to 2015, thereby indicating an increasing influence on the increase in carbon emissions. Changes in occupational structure are critical drivers of carbon emissions. The state-owned economy dominates the national economy and affects the functional employment structure of China's population.

Table 11. PLS regression estimates

Variables	*Non-standard coefficient*	*Standard coefficient*
C	0.886	18.662
lnPSIZE	0.011	0.037
lnCDR	-0.088	-0.390
lnEDR	-0.021	-0.077
lnES	0.017	0.046
lnOS	-0.021	-0.231
lnPD	-0.013	-0.041
lnGS	-1.158	-0.248
lnPGDP	0.004	0.108
lnECI	0.013	0.152
lnER	-0.181	-0.244
lnURB	0.018	0.030
R2X(cum)	1.000	
R2Y(cum)	0.931	
Q2(cum)	0.804	

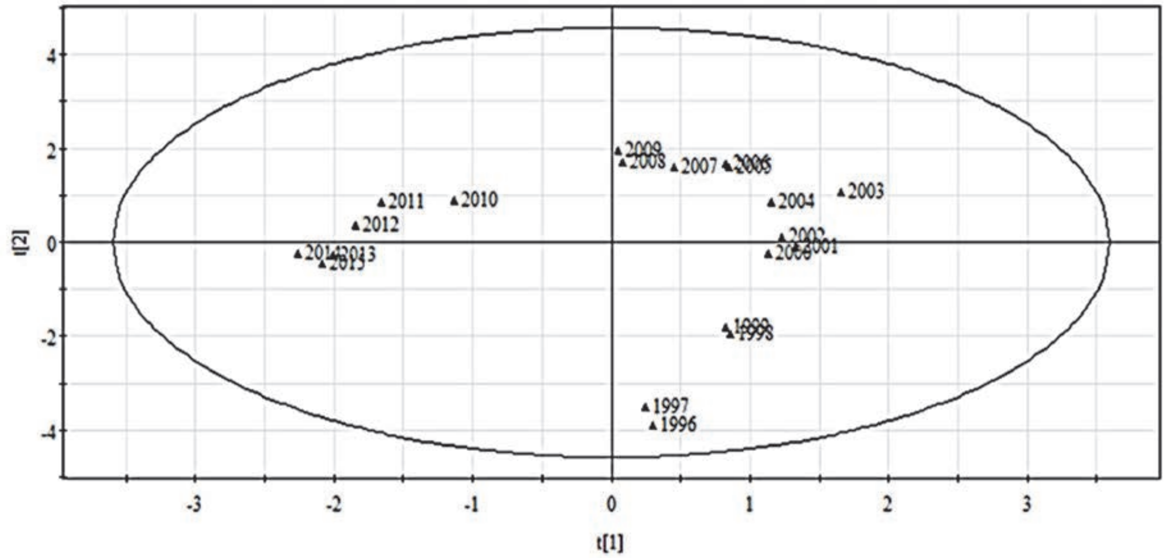

Fig. 4. QUOTE t1/t2 oval plot

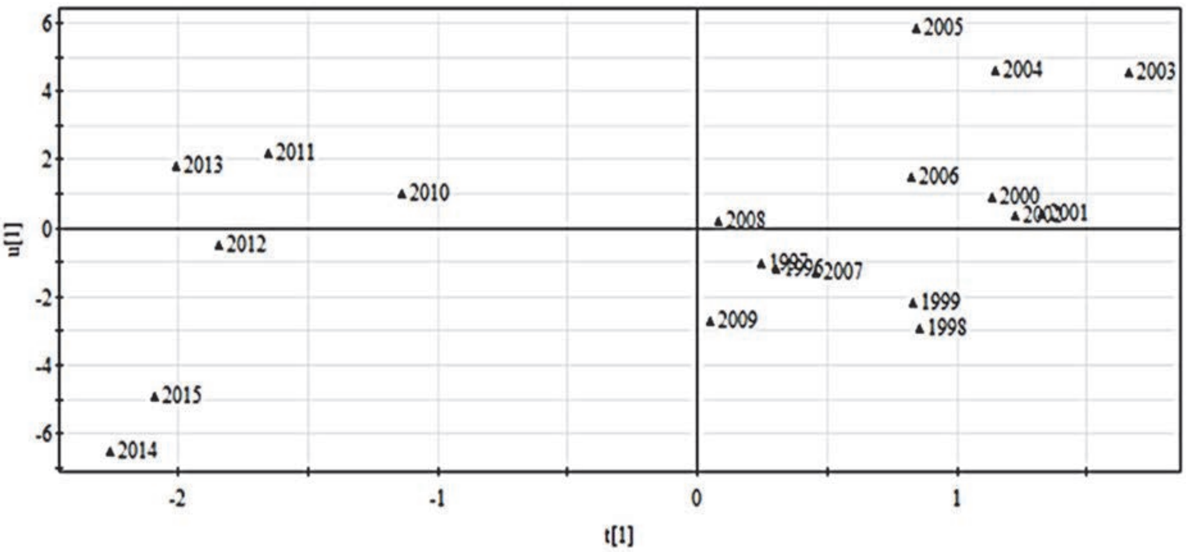

Fig. 5. t1/u1 QUOTE plot

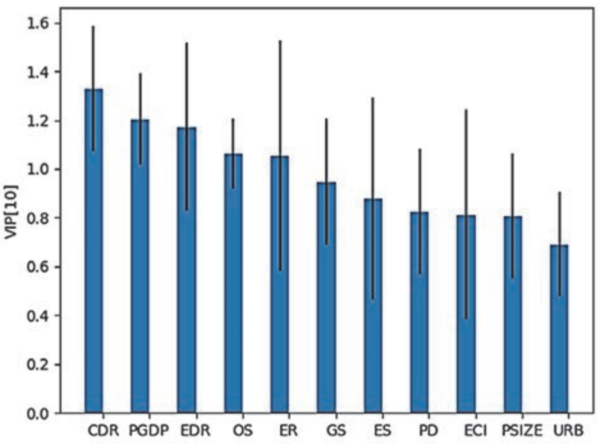

Fig. 6. VIP Histogram

Table 12. VIP values

Variable	*VIP Value*
lnPSIZE	0.805
lnCDR	1.327
lnEDR	1.1731
lnES	0.880
lnOS	1.064
lnPD	0.824
lnGS	0.948
lnPGDP	1.204
lnECI	0.813
lnER	1.053
lnURB	0.690

Given the continuous marketization of the Chinese economy, the proportion of state-owned economy decreased sharply. Fig. 7 shows that the share of employment in state-owned organizations in Shanghai decreased from 61.10% in 1996 to 8.4% in 2015, thereby representing a sharp decline of 86.25%. The PLS regression results indicated that carbon emission will increase by 0.021% when the proportion of employed persons in state-owned units decreases by 1%. This finding is similar to that of Guo and Sun (2017). One explanation may be the economic inefficiency of the state-owned economy that spurred and accelerated the development of the market economy in a real sense, increased the energy consumption and further heightened carbon emissions. Therefore, Shanghai is facing significant pressure on carbon emissions from the perspective of occupational structure. A substantial increase in the proportion of college graduates and above has a remarkable effect on carbon emissions. The analytical results show that every 1% increase in the proportion of college graduates in Shanghai will increase carbon emission by 0.017%.

On the one hand, improvements in population quality lead to technological progress. The associated energy utilization convenience can boost energy consumption and carbon emissions of residents (Tang et al., 2017). On the other hand, the experiences of developed countries show that the educated population tends to have high-consumption lifestyle and energy use behaviour (Becken et al., 2003; Smeaton et al., 1998; Stevens and Weale, 2003). The results of the demographic structure have been supported by Katircioğlu (2014), who argued that high-quality staff will insignificantly replace the existing staff. Therefore, the number of employees will not reduce significantly alongside the improvement of their education.

The improvement in the quality of the population in the long and short terms will increase the consumption of electricity and oil by driving the development of economic enterprises, such as restaurants, travel agencies and dry cleaners. The gender structure shows constricting effects on carbon emissions. That is, a substantial proportion of females indicate increased carbon emissions. This concept can be analyzed from the perspective of social production and consumption behaviour.

Although the decline in the proportion of females may reduce the labour input in energy-intensive industries and carbon emissions, changes in the population gender structure are even likely to play a role in the consumption market. Fig. 7 shows that the male-to-female ratio in Shanghai continues to decline.

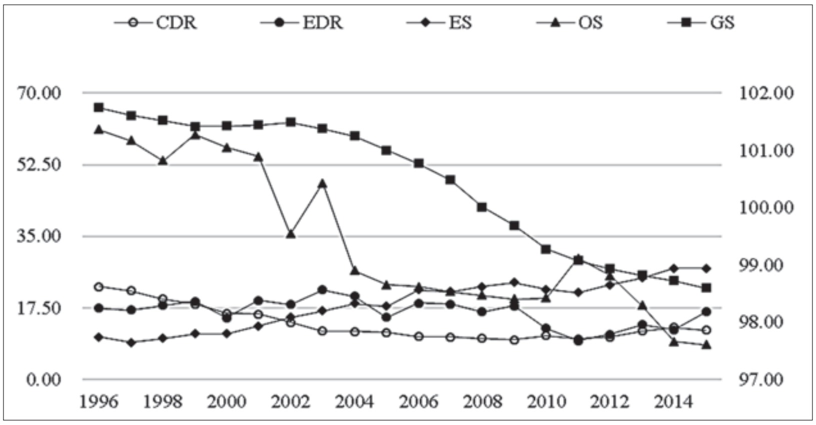

Fig. 7. Changes of population structure in Shanghai from 1996 to 2015 (Note: *CDR, EDR, ES and OS refer to Child Dependency Ratio, Elderly Dependency Ratio, Population Education Structure and Population Occupation Structure, respectively (Refer to the left axis: %). GS refers to Gender Structure of Population (Refer to the right axis: %)*

Women are likely to increase material consumption owing to the differences in consumer psychology and philosophy. This situation leads to an increase in energy pressure in production, a direct or indirect increase in social energy consumption and eventually an increase in carbon emissions. Consequently, the influences of gender structure on carbon emissions should not be underestimated.

Population size increases carbon emissions. Rapid population growth spurs the expansion of needs for housing, transportation, energy and resources. Population size also affects the total social production and consumption, thereby resulting in an increase in energy consumption and carbon emissions. The regression results are consistent with the observations and theoretical derivation but are less critical than the aforementioned demographic factors.

Carbon emission reduction is consistent with the increase in population density. Population density is a measurement of population per unit area, reflects the geographical distribution of the population and a basic demographic factor that has been recognised by the United Nations Population Fund (2009) as contributory to carbon emissions. The elasticity coefficient is negative, which is consistent with Liddle (2004, 2014). The results indicate that the increase in population density can reduce carbon emissions, mainly because of the scale effect of population density that can affect the average propensity to consume and reduce the per capita consumption. Therefore, high population density, such as compact city planning, is an effective solution to mitigate carbon emissions. GDP per capita, energy consumption intensity and environmental regulation are control variables in the demographic analytical model that affect carbon emissions. The PLS regression results show that the energy consumption intensity and environmental regulation will change carbon emission by 0.004%, 0.013% and -0.181% for every 1% change in GDP per capita. Fig. 8 shows that the GDP per capita in Shanghai increased from 20.647 Yuan in 1996 to 79.800 yuan in 2015, thereby indicating an increment of 286.5% and average annual growth rate of 14.33%. The rapid growth of GDP per capita shows that the people's standards of living have been significantly improved. Shanghai's economic development over the past two decades also shows that GDP growth and the associated enhancement of standards of living are key contributors to the significant increase in production and consumption of high-energy-consuming products. These factors interacted to become the inner driving force of Shanghai's carbon emissions.

A positive correlation exists between Shanghai's GDP per capita and carbon emissions, thereby indicating that this city is still in the rising phase of the Kuznets curve. Economists Grossman and Krueger proposed the Environmental Kuznets Curve in 1995 and argued that an inverted 'U-shaped' relationship exists between economic growth and environmental pollution. Subsequently, the carbon emission environmental Kuznets curve was proposed to describe the relationship between economic growth and carbon emissions. That is, at a low level of economic development, carbon emissions will increase with an increase in the per capita GDP growth. When the level of economic development is high, carbon emissions will decrease with the increase of per capita GDP, thereby showing an inverted 'U-shaped' relationship.

The energy consumption intensity, as an indicator of the level of energy technology, decreased remarkably from 1.38 t coal in 1996 to 0.19 t coal per 1.000.000 yuan in 2015. This finding indicates that Shanghai's energy technology and the energy use efficiency continues to significantly improve. These circumstances inevitably become the key fundamentals to achieving the targets of energy saving and emission abatement in Shanghai. The intensity of energy consumption in Shanghai is positively correlated with carbon emissions, thereby indicating that the increase in energy use efficiency can reduce carbon emissions. Moreover, an energy-saving effect can be observed.

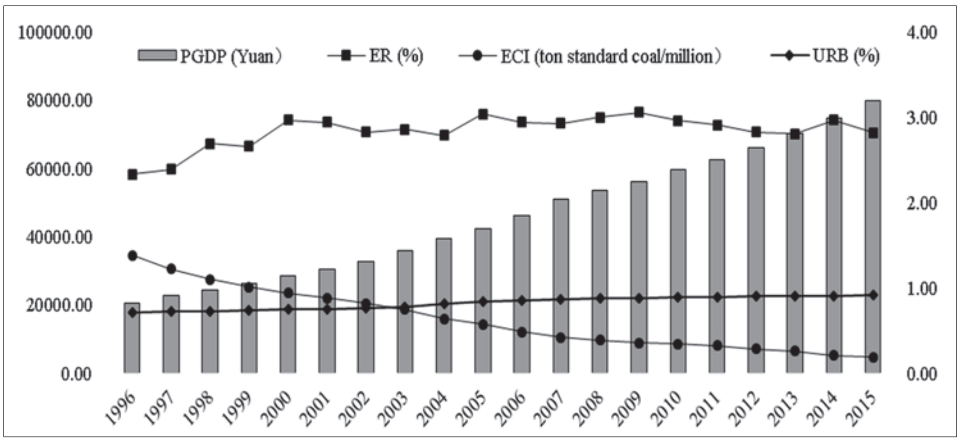

Fig. 8. Trends of wealth and technology in Shanghai during 1996-2015
Note: PGDP *refers to Per Capita GDP (Refer to the left axis: RMB Yuan). ER, ECI and URB refer to the right axis*

The energy-saving effect is a type of rebound effect, which means that technological progress will result in an increase in production efficiency. This situation has resulted in a decline in production cost, thereby leading to increased consumption. Therefore, the increasing excessive energy consumption would offset the energy savings brought by the improvement of efficiency.

Environmental regulation is the internalization of environmental externalities. Porter suggested that the environmental regulation policy formulated by the government can stimulate the innovation vitality of the enterprise. Thus, the companies obtained benefits, which partially or completely offset the enterprise cost brought by environmental regulation. Accordingly, the enterprise becomes competitive in the market. The 'Porter hypothesis' provides that reasonable environmental regulation can produce 'innovation compensation effects'. 'Innovation compensation effects' indicate that environmental regulation policies can provide enterprises with information and motivation for technological innovation to enhance their competitiveness. Reasonable environmental regulation can promote technological innovation and realise the coordinated development of the economy and environment. Fig. 8 shows that *ER* denotes the investment in environmental protection, representing the level of environmental regulation. A steady increase in Shanghai's *ER* has been noted over the past 20 years, and environmental protection work is steadily advancing. Combined with the statement on the energy consumption intensity, environmental regulation is conducive to technological innovation, thereby confirming the validity of the 'Porter hypothesis.' Primary goal in carbon emission abatements has been achieved.

Table 11 shows that the non-standard coefficient of lnURB is 0.018. However, the VIP value of lnURB is 0.69, which is below the statistical significance level of 0.8 (Table 12). This finding indicates that the urbanization rate is not a driving factor for the increase in carbon emission in Shanghai. The underlying reason is as follows. Shanghai has been one of the most urbanized cities in China since the previous decades, when population density and economic agglomeration reached a relatively high level. In recent years, Shanghai's urbanization rate has approached its peak and maintained a stable level. Therefore, the effects of urbanization on carbon emission in Shanghai are weak and statistically insignificant.

5. Conclusions and recommendations

This study investigates the effects of demographic factors on urban carbon emissions. A wide array of factors includes population size, age, occupation, education, gender and population density. The contributing factors are identified, and the magnitudes of effects are estimated on the basis of the STIRPAT model and regression technique, such as PLS. This study expands the theoretical underpinnings and provides extensive policy implications for emission abatement at the municipal levels.

Several important findings are derived. (1) The child dependency ratio, old age dependency ratio and occupational structure are critical and have adverse effects on carbon emission. (2) The elasticity coefficients of the educational and gender structures are 0.017 and -1.158, respectively. (3) Population density and size are also important determining factors of carbon emission, albeit with limited strong effects. Increasing population density reduces carbon emissions, whereas expanding population is an important contributor of carbon emissions. (4) GDP per capita, environmental regulation and energy use intensity are the key economic and technological factors that significantly affect carbon emissions. Although environmental regulation has a constricting effect, it cannot adequately offset the positive effect of GDP per capita and energy intensity on carbon emissions. Specifically, the elasticity coefficients of GDP per capita and energy use intensity are 0.004 and 0.013, respectively.

Effective policy recommendations are provided on the basis of the research findings.

(1) Encouraging low-carbon consumption behaviours. Consumption is the key driving force for carbon emission. Hence, transforming consumption patterns towards low-carbon products and lifestyle is vital to achieve the goal of carbon emission reduction. The awareness of environmental friendliness and sustainability should be encouraged, fostered and strengthened in public. Low-carbon consumption behaviors, such as recycling measures, sharing economy and public transportation, should be popularized by the release of relation regulations and subsidies.

(2) Optimizing urban planning and layouts. The population density of a city reflects the distribution of residents and business activities, and is generally affected by urban planning and layout. An appropriate population density is vital for the efficiency of public transportation and other urban infrastructures. Specifically, a reasonable level of population density can reduce the fiscal expenditure and costs of time in public transportation, such as subways and buses. In the energy supply infrastructures, such as heating and gas, a balanced population distribution can improve energy efficiency and further reduce carbon emissions.

(3) Encouraging low-carbon technological innovation. Technological innovation is the cornerstone for improving energy saving and carbon emission reduction. Collective commitments and effort by the government and enterprise are imperatively needed to foster low-carbon technological innovation. On the one hand, fiscal support, such as subsidies and tax deductions, by the government are recommended to stimulate and nurture low-carbon technological innovation. On the other hand, close cooperation between enterprises and

scientific research institutions is expected to invent, improve and commercialize energy-saving and emission-reducing technologies.

(4) Promoting industrial transformation and upgrading. Highly polluting and emission-intensive enterprises with backward production facilities should be eliminated to ease the environmental constraints. The proportion of low-value-added industries should also be appropriately reduced. The electricity industry must accelerate energy transition toward the deployment and commercialization of clean and renewable energy, such as hydro, wind and solar energy.

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