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The impacts of population change on carbon emissions in China during 1978–2008

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ABSTRACT

This study examines the impacts of population size, population structure, and consumption level on carbon emissions in China from 1978 to 2008. To this end, we expanded the stochastic impacts by regression on population, affluence, and technology model and used the ridge regression method, which overcomes the negative influences of multicollinearity among independent variables under acceptable bias. Results reveal that changes in consumption level and population structure were the major impact factors, not changes in population size. Consumption level and carbon emissions were highly correlated. In terms of population structure, urbanization, population age, and household size had distinct effects on carbon emissions. Urbanization increased carbon emissions, while the effect of age acted primarily through the expansion of the labor force and consequent overall economic growth. Shrinking household size increased residential consumption, resulting in higher carbon emissions. Households, rather than individuals, are a more reasonable explanation for the demographic impact on carbon emissions. Potential social policies for low carbon development are also discussed.

1. Introduction

During the past 200 years, global population, global income (gross domestic product), and carbon emissions have increased 6, 70, and 20 times, respectively (Jiang and Hardee, 2009). The history of most developed countries shows that in the development process, industry accounts for the largest proportion of carbon emissions. However, recent statistics reveal that since the 1990s, the contribution of residential energy consumption in some developed countries to carbon emissions has exceeded that of industrial sectors. Therefore, the impacts of population growth and associated residential consumption on carbon emissions have attracted increasing research interest (Bin and Dowlatabadi, 2005; Druckman and Jackson, 2009; Weber and Adriaan, 2000).

Clearly identifying the relationship between population and carbon emissions is highly challenging primarily because of the wide-ranging effects of population on carbon emissions. These effects usually exert indirect influence over consumption, production, technology, and trade, among others. In terms of population characteristics, almost all important demographic factors, including population size, structure, quality, distribution, and migration, constantly change, thereby imposing complicated and variable effects on carbon emissions. Studies have thus far concentrated on the relationship between population growth and emission increase, as well as on the impacts of population structure, including age structure, urbanization level, regional distribution, and household composition, on carbon emissions.

The approaches to studying the relationship between population and carbon emissions can be categorized into two: investigating the causalities and mechanisms of interaction between population and carbon emissions, and quantitatively evaluating the impacts of population growth on carbon emission increase. Birdsall (1992) summarized two principal mechanisms through which population growth in developing countries contributes to greenhouse gas emissions. The first is the effect of large populations on fossil fuel consumption—an effect that stems from the increased energy demand for power generation, industry, and transport. The second mechanism is the effect of population growth-related emissions on deforestation. The author concluded that reductions in population growth matter, but are not the key factor in leveling off carbon emissions. Knapp and Mookerjee (1996) discussed the nature of the relationship between global population growth and CO_2 emissions by conducting a Granger causality test on annual data for 1880–1989. The results suggest no long-term equilibrium relationship, but imply a short-term dynamic relationship between CO_2 emissions and population growth.

The IPAT identity (Ehrlish and Holdren, 1971) has been extensively used in the quantitative evaluation of the effects of population growth on carbon emission increase. According to the principle of the formula and its stochastic form, the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model, the main driving forces behind environmental impact (I) are population (P), affluence (A), and technology (T). Researchers typically assess the impact of population on carbon emissions by altering population size while keeping other variables constant. Shi (2003) examined 1975–1996 data on 93 countries using the IPAT model and found that the impact of population change on carbon emissions is considerably more pronounced in developing countries than in developed nations. The author also determined that

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the elasticity of emissions with respect to global population change was 1.42. Cole and Neumayer (2004) and Rosa et al. (2004) also measured the impact of population on carbon emissions using the IPAT model, and found that the elasticities of emissions in relation to population were 0.98 and 1.02, respectively. Wei (2011) discussed the role of technology in the STIRPAT model, and argued that the different functional forms of STIRPAT can explain the differences among estimates in studies on the environmental impacts of population and affluence.

The effects of population on carbon emissions are commonly embodied in production and consumption behaviors, which are closely tied to population size and population structure. Satterthwaite (2009) investigated the CO_2 emission levels in various nations for the periods 1950–1980 and 1980–2005. The results show little association between rapid population growth and high emission increase because nations with very low emissions per capita are mostly those with the highest population growth rates. Jiang and Hardee (2009) argued that consumption and production patterns among various population groups differ. In almost all climate models, however, population size is the only demographic variable considered. The assumption behind this treatment is that each individual in a population shares the same production and consumption behavior, but this assumption may be inaccurate and misleading. Hence, paying more attention to the variables of population structure is necessary in investigating the impact of population on carbon emissions.

Researchers have closely monitored urbanization levels because these are highly relevant to residential consumption scale and consumption structure. Urbanization generally affects carbon emissions in three ways. First, the use of energy in production is concentrated primarily in cities, and residential consumption level increases in line with urbanization. Both situations increase energy demand, resulting in carbon emission increase, given that the energy structure remains the same. Second, the requirements for infrastructure and dwelling houses grow along with urbanization, increasing the demand for building materials (especially cement products), which are important sources of carbon emissions. Third, urbanization involves the conversion of grasslands and woodlands, these land-use changes increase carbon emissions. Poumanyvong and Kaneko (2010) empirically investigated the effects of urbanization on energy use and CO_2 emissions. In the investigation, the authors considered different development stages using the STIRPAT model, as well as a balanced panel dataset that covers 1975–2005 and includes 99 countries. The findings suggest that the impact of urbanization on carbon emissions is positive for all income groups, but that this effect is more pronounced in the middle-income group than in the other income groups. Pachauri and Jiang (2008) compared the household energy transitions in China and India since the 1980s by analyzing aggregate statistics and nationally representative household surveys. The authors revealed that compared with rural households, the urban households in both nations consumed a disproportionately large share of commercial energy and were much further along in the transition to modern energy. Satterthwaite (2009) considered the implications of population growth and urbanization for climate change between 1980 and 2005. The author concluded that the increasing number of urban consumers and their consumption levels, not population growth, drive the increase in greenhouse gas emissions.

Studies on the relationship between age structure and carbon emissions focus on the accelerated global aging process. Research in this area is still at its infancy. Fan et al. (2006) analyzed the impact of population, affluence, and technology on the total CO_2 emissions of countries at different income levels at the global scale over the period 1975–2000. The results show that population age (15–64 years) has less impact on CO_2 emissions than do population size, affluence, and technology. Dalton et al. (2008) incorporated population age structure into an energy–economic growth model with multiple dynasties of heterogeneous households to estimate and compare the effects of aging populations and technical change on the baseline paths of US energy use and CO_2 emissions. The authors showed that an aging population reduces long-term emissions by almost 40% in a low-population scenario, and that the effects of the aging process on emissions can be as large as, or larger than, those of technical change in some cases, given a closed economy, fixed substitution elasticity, and fixed labor supply over time.

The effect of changes in household size on carbon emissions is another research focus. Given a fixed population size, a change in the number of households due to a change in household size can influence consumption scale and consumption structure, thereby significantly affecting carbon emissions. Thus far, there is no commonly accepted standard for defining household types in terms of environmental influence, and the effect of changes in household size on carbon emissions remains uncertain. Dalton et al. (2007) incorporated household size into the population–environment–technology model to simulate economic growth, as well as changes in the consumption of various goods, direct and indirect energy demand, and carbon emissions over the next 100 years. Jiang and Hardee (2009) discussed the impact of shrinking household size on carbon emissions and argued that households, rather than individuals in a population, should be used as the variable in analyzing demographic impact on emissions. This approach is favorable considering that households are the units of consumption, and possibly also the units of production in developing societies.

China is currently at a demographic turning point, i.e., changing from an agricultural into an urban society, from a young society to an old one, and from a society attached to land to a more floating one (Peng, 2011). Population dynamics and changes in consumption patterns have influenced and will undoubtedly continue to influence China's energy use and consequent carbon emissions. Examining these issues will facilitate improvements in decision making for low carbon development. In this study, therefore, we incorporate population structure (age structure, urbanization level, and household size) into the STIRPAT model to examine the impacts of population size, population structure, and consumption level on carbon emissions. By doing so, we hope to more completely and accurately reflect the impacts of population change on carbon emissions. To overcome the negative influences of multicollinearity among independent variables, we use the ridge regression method to estimate the coefficients of the model. As an empirical case study, the impacts of population and consumption on emissions in China from 1978 to 2008 are quantitatively assessed and analyzed. Corresponding policy suggestions for energy conservation and emission reduction in China are proposed.

2. Model

The IPAT identity (Ehrlish and Holdren, 1971) is an equation that is commonly used to analyze the impacts of human behavior on environmental pressure. The equation is expressed as

$$I = PAT, \tag{1}$$

where I represents environmental impact, P represents population, A stands for affluence, and T denotes technology.

The IPAT identity is an accounting model, in which one term is derived from the values of the three other terms. The model requires data on only any three of the four variables for one or a few observational units, and it can only be used to measure the constant proportional impacts of the independent variables on the dependent variable. To overcome this limitation, Dietz and Rosa (1994) established the STIRPAT model by reformulating the IPAT identity into stochastic form:

$$I = aP^bA^cT^de, \tag{2}$$

where I, P, A, and T have the same definitions as in the IPAT identity; a, b, c, and d are coefficients; and e is a residual term. In this reformulation, data on I, P, A, and T can be used to estimate a, b, c, d, and e with statistical regression methods. The reformulated version can convert the IPAT accounting model into a general linear model, in which statistical methods can be applied to test hypotheses and assess the non-proportionate importance of each influencing factor. As a special case, the stochastic version can be converted back to the original model given that $a=b=c=d=e=1$.

York et al. (2003) developed an additive regression model in which all variables are in logarithmic form, facilitating estimation and hypothesis testing. York et al. (2003) and Wei (2011) argued that in the typical application of the STIRPAT model, T should be included in the error term, rather than separately estimated, for consistency with the IPAT model, where T is solved to balance I, P, and A. The modified STIRPAT model is expressed as follows:

$$\ln I = \ln a + b(\ln P) + c(\ln A) + e. \tag{3}$$

According to the concept of ecological elasticity (York et al., 2003), coefficients b and c from Eq. (3) are the population and affluence elasticities, respectively. These elasticities refer to the responsiveness or sensitivity of environmental impacts to changes in corresponding impact factors. For instance, coefficient b indicates percentage change in I in response to a 1% change in population, with other factors held constant.

To comprehensively observe the impact of population on carbon emissions, we incorporate the indicators of population structure, including urbanization level, age structure, and household size, into the STIRPAT model to come up with the following expanded form:

$$\ln I = \ln a + b_s(\ln Ps) + b_c(\ln Pu) + b_a(\ln Pw) + b_f(\ln Ph) + c(\ln A) + e, \tag{4}$$

where

- I refers to carbon emissions;
- Ps denotes population size;
- Pu, Pw, and Ph are the three factors that indicate population structure; that is, Pu for urbanization rate, Pw for the proportion of working age (16–64 years old) population, and Ph for household size, which is indicated by the average number of household members;
- A represents per capita annual expenditure;
- e is a residual term.

3. Data description and data testing

3.1. Data description

The population, consumption, and carbon emissions in China from 1978 to 2008 are summarized in Table 1. Data on carbon emissions from fossil fuels and cement come from the data center of the Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory, USA (CDIAC, 2011). Population and consumption data are obtained from the China Statistical Yearbook, released by China's National Bureau of Statistics. Expenditure data are adjusted to fit the fixed prices in 2000.

Fig. 1 shows the changing rates of all the variables, with 1978 as the base year. Almost all the variables were non-stationary, with a continuous uptrend or downtrend during the period. Among all the variables, per capita expenditure presented the fastest growth at 8.17 times, followed by carbon emissions (3.72 times) and urbanization rate (1.55 times). Population size and proportion of working age population increased by 37.96% and 22.35%, respectively. Average household size showed a continuous shrinking trend, decreasing by 32.24% over the period.

Taking the logarithm of data can reduce non-stationarity, as well as linearize variables, so that the disadvantage presented by variables having different measurement units is eliminated; thus, all the data used in the current work are transformed into natural logarithmic series.

3.2. Stationarity test

The acceptability of a regression result is commonly based on the premise that the series used in the regression model are stationary or co-integrated if the series are non-stationary; otherwise inauthentic regression may occur. Furthermore, multicollinearity among independent variables can cause large variances in estimated coefficients and decrease the accuracy of estimated equations; a multicollinearity test should be performed on independent variables.

The augmented Dickey–Fuller (ADF) unit root test is typically used to examine the stationarity of time series, in which a high-order autoregressive model with an intercept term is established (Maddala and Kim, 1998). Taking the ADF test on series ln$I$ as an example, we express the test equation with the constant term, as well as the trend and intercept terms, as follows:

$$\Delta \ln I_t = \alpha + \beta t + \delta \ln I_{t-1} + \sum_{i=1}^{k} \beta_i \Delta \ln I_{t-i} + \varepsilon_t, \tag{5}$$

where α, β, and δ are coefficients; ε is a residual term; and k is the lag length, which turns the residual term into a stochastic variable.

The null hypothesis $H0$ is $\delta=0$; i.e., at least one unit root exists, causing the non-stationarity of the series. The test is conducted with three formulations: ($\alpha\neq0, \beta\neq0$), ($\alpha=0, \beta\neq0$), and ($\alpha=0, \beta=0$). As long as one of the three models rejects the null hypothesis, the series are considered stationary. However, when the results of all the three models do not reject the null hypothesis, the series are regarded as non-stationary.

The results of the stationary test on all the series are summarized in Table 2.

According to the results, series lnPu, lnPw, lnPh, and ln$A$ are I (0) or stationary. Series lnPs and ln$I$ are I (1), indicating that they are first-order integrated series. Hence, the co-integration between the two series must be examined to determine whether they satisfy the precondition of regression analysis.

3.3. Co-integration test

Series lnPs and ln$I$ are both I (1); thus, they satisfy the precondition of the same integrated order for conducting a bivariate co-integration test. On the basis of the Engle–Granger test method (Engle and Granger, 1987), we express the co-integration regression equation as

$$\ln I_t = \alpha + \beta \ln Ps_t + \varepsilon_t. \tag{6}$$

Denoting the estimated regression coefficients of Eq. (8) as $\hat{\alpha}$ and $\hat{\beta}$, the estimated residual series is then expressed as follows:

$$\hat{\varepsilon} = \ln I_t - \hat{\alpha} - \hat{\beta} \ln Ps_t. \tag{7}$$

If $\hat{\varepsilon}$ is I (0), then ln$I$ and lnPs are co-integrated.

Coefficients $\hat{\alpha}$ and $\hat{\beta}$ are estimated by ordinary least squares (OLS), and then the unit root test is performed on estimated residual series $\hat{\varepsilon}$ using the ADF test method. The results are shown in Table 3.

Table 3 shows that the calculated ADF t-statistic of series $\hat{\varepsilon}$ was −1.8455, which is less than the critical value at the 10% significance level. Hence, the result rejects the null hypothesis, indicating that series $\hat{\varepsilon}$ without a unit root is stationary; i.e., $\hat{\varepsilon}$ is I (0). Therefore, series ln$I$ and lnPs are co-integrated.

We examine the Granger causality between series ln$I$ and lnPs. The bivariant regression models for the Granger causality test are expressed as follows:

$$\ln I_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln I_{t-i} + \sum_{i=1}^{k} \beta_i \ln Ps_{t-i}, \tag{8}$$

Table 1
Population, consumption, and carbon emissions in China (1978–2008).

Year	Carbon emissions (MtC)[a]	Population size (10^4)	Urbanization rate (%)	Proportion of working age population (%)	Household size (person/household)	Per capita expenditure (CNY)
1978	40,768.9	96,259	17.92	59.50	4.66	740
1979	41,648.9	97,542	18.96%	60.00%	4.65	791
1980	40,698.6	98,705	19.39%	60.50%	4.61	862
1981	40,292.5	100,072	20.16%	61.00%	4.54	934
1982	43,122.8	101,654	21.13%	61.50%	4.51	997
1983	45,468.6	103,008	21.62%	62.37%	4.46	1079
1984	49,433.6	104,357	23.01%	63.24%	4.41	1207
1985	53,587.3	105,851	23.71%	64.12%	4.33	1370
1986	56,348.0	107,507	24.52%	64.99%	4.24	1435
1987	60,123.0	109,300	25.32%	65.86%	4.15	1520
1988	64,445.3	111,026	25.81%	66.15%	4.05	1638
1989	65,473.6	112,704	26.21%	66.45%	3.97	1635
1990	65,855.4	114,333	26.41	66.74	3.93	1695
1991	69,147.7	115,823	26.94	66.30	3.89	1842
1992	72,143.5	117,171	27.46	66.20	3.85	2086
1993	77,019.8	118,517	27.99	66.70	3.81	2262
1994	81,807.1	119,850	28.51	66.60	3.78	2367
1995	88,471.7	121,121	29.04	67.20	3.74	2553
1996	92,597.1	122,389	30.48	67.20	3.72	2793
1997	91,486.8	123,626	31.91	67.50	3.64	2919
1998	86,614.1	124,761	33.35	67.60	3.63	3091
1999	90,501.7	125,786	34.78	67.70	3.58	3346
2000	92,886.8	126,743	36.22	70.15	3.44	3632
2001	95,144.0	127,627	37.66	70.40	3.42	3855
2002	100,957.7	128,453	39.09	70.30	3.39	4125
2003	118,724.4	129,227	40.53	70.40	3.38	4415
2004	139,067.5	129,988	41.76	70.92	3.31	4773
2005	153,424.4	130,756	42.99	72.04	3.24	5142
2006	166,458.9	131,448	43.90	72.32	3.17	5636
2007	180,165.9	132,129	44.94	72.53	3.17	6239
2008	192,268.7	132,802	45.68	72.80	3.16	6782

Sources: The carbon emission data are obtained from the CDIAC (2011); the data on population and consumption are from the China Statistical Yearbook, with some interpolation for the missing data on working age population for several years in the 1980s; the expenditure data are adjusted to fit the fixed prices in 2000.
[a] MtC refers to million-ton carbon

$$\ln Ps_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln Ps_{t-i} + \sum_{i=1}^{k} \beta_i \ln I_{t-i}. \tag{9}$$

The null hypothesis is $\beta_1 = \beta_2 = \ldots = \beta_k = 0$ given that the maximal lag length is $k = 2$. The test results are shown in Table 4.

The first hypothesis states that series ln*Ps* is not the Granger cause of series ln*I*; the concomitant significance of this hypothesis was 0.1619, suggesting that ln*Ps* is the Granger cause of ln*I*, with 83.81% significance. The concomitant significance for the second hypothesis was 0.8752, indicating that ln*I* is not the Granger cause of ln*Ps*.

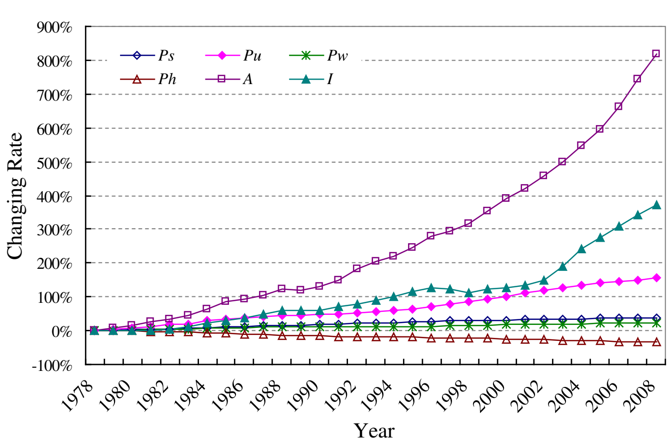

Fig. 1. Changing rates of population, consumption, and carbon emissions in China (1978–2008). Sources: same as in Table 1.

3.4. Multicollinearity test

Multicollinearity refers to a situation in which two or more independent variables in a multiple regression model are highly linearly related (Donald and Robert, 1967). In this situation, the standard errors of the affected coefficients tend to be large, and the coefficient estimates may change erratically in response to small changes in data. Such erratic changes result in the possible failure of the regression model to provide valid results on individual variables.

The multicollinearity of the independent variables in the model is examined by OLS regression and by valuing the variance inflation factors (VIFs) of the variables. Taking the test on multicollinearity among ln*Ps* and the other variables as an example, we use the OLS method to regress ln*Ps* on the other independent variables. As shown in Table 5, the estimated coefficient of determination (R^2) of the model was 0.9803 and the *F*-test was highly significant, with an *F*-statistic of 323.8751 at the 0.1% significance level. The VIFs of the variables ranged from 29.6551 to 173.5764, which are considerably greater than 10. Given that Marquardt (1970) used a VIF greater than 10 as a guideline for severe multicollinearity, we can conclude that a high degree of

Table 2
Results of the stationary test using the ADF test.

Variable	Difference order	Exogenous (α, β, k)	*t*-Statistic	Significance level	Test critical value	Verdict
ln*Ps*	1	(α, β, 1)	−3.7195	5%	−3.5806	*I* (1)
ln*Pu*	0	(0, 0, 1)	−2.9440	1%	−2.6471	*I* (0)
ln*Pw*	0	(0, 0, 1)	−3.2563	1%	−2.6471	*I* (0)
ln*Ph*	0	(0, 0, 1)	−4.0599	1%	2.6471	*I* (0)
ln*A*	0	(α, β, 1)	−3.2983	10%	−3.2217	*I* (0)
ln*I*	1	(α, 0, 4)	−3.2972	5%	−2.9862	*I* (1)

Table 3
Results of the unit root test on $\hat{\varepsilon}$.

	Significance	t-Statistic	Probability
ADF test statistic		−1.8455	0.0626
Test critical values:	1% level	−2.6471	
	5% level	−1.9529	
	10% level	−1.6100	

multicollinearity exists among ln*Ps* and the other independent variables in Eq. (4).

The same multicollinearity test was performed on the other independent variables; all the results indicate a high degree of multicollinearity among these variables.

4. Regression estimation

4.1. Ridge regression

The danger of multicollinearity primarily stems from its generation of large standard errors among related independent variables; these errors are characterized by large variances in model parameters, making the model unstable. Given that these standard errors are significantly reduced using a curtain method, the negative consequences of such errors can be effectively eliminated even when multicollinearity remains in the model. Ridge regression, which can obtain acceptably biased estimates with smaller mean square errors in independent variables through tradeoffs in bias–variance, is one of the most effective solutions for multicollinearity.

Hoerl and Kennard (1970) explicitly specified the estimation procedure for ridge regression as an improved substitute for traditional OLS regression. Consider the standard model for multiple linear regression,

$$Y = X\beta + \varepsilon, \tag{10}$$

where X is $(n \times p)$ and is of rank p, β is $(p \times 1)$ and unknown, $E[\varepsilon]=0$, and $E[\varepsilon\varepsilon'] = \delta^2 I$. The unbiased estimate of β is normally given by

$$\hat{\beta} = (X'X)^{-1}X'Y. \tag{11}$$

When a high degree of multicollinearity exists among X, the $X'X$ matrix is ill-conditioned; i.e., the value of its determinant $|X'X| \approx 0$, and attempts to calculate the $(X'X)^{-1}$ matrix may be highly sensitive to slight variations in data. In controlling the inflation and general instability associated with least squares estimates, as well as in estimating β, the ridge regression that incorporates small positive quantity k to the diagonal of normalized independent variable matrix $X'X$ uses

$$\hat{\beta}^* = (X'X + kI)^{-1}X'Y. \tag{12}$$

This equation creates a variance in parameter estimates that is less than that estimated by OLS regression under the condition $k \geq 0$.

Therefore, choosing an appropriate k, accepting minimal bias, and substantially reducing variance are possible, thereby remarkably improving estimation. Ridge regression can be converted back to OLS regression as a special case given that $k=0$ (Hoerl and Kennard, 1970).

Table 4
Results of the Granger causality test on ln*I* and ln*Ps*.

Null hypothesis:	Obs	F-statistic	Probability
ln*Ps* is not the Granger cause of ln*I*	29	1.9663	0.1619
ln*I* is not the Granger cause of ln*Ps*		0.1340	0.8752

Table 5
Multicollinearity test on ln*Ps* and other independent variables by OLS.

Adjusted R^2			0.9803
Standard error			0.0155
F-statistic			323.8751***

ln*Ps*	Coefficient	t-Statistic	VIF
ln*Pu*	−0.2706* (0.1116)	−2.4252	120.7909
ln*Pw*	0.3378 (0.2650)	1.2749	29.6551
ln*Ph*	−0.5381* (0.2262)	−2.3791	100.8291
ln*A*	0.1383* (0.0573)	2.4129	173.5764
Constant	11.1249*** (0.7234)	15.3781	

Standard errors are in parentheses.
*** $p<0.001$ (two-tailed test).
* $p<0.05$ (two-tailed test).

Considering that the relationship of a ridge estimate to an ordinary estimate is given as

$$\hat{\beta}^* = \left[I + k(X'X)^{-1}\right]^{-1}\hat{\beta}, \tag{13}$$

we can derive the expression for estimating the bias introduced when $\hat{\beta}^*$ is used rather than $\hat{\beta}$ as follows:

$$bias = \left|\left[I + k(X'X)^{-1}\right]^{-1}\right|. \tag{14}$$

4.2. Estimation results

The ridge traces estimated for the expanded STIRPAT model are shown in Fig. 2. The results for all the estimated normalized coefficients are summarized in Table 6.

As shown in Fig. 2, when $k=0.20$, the coefficients of the independent variables tend to be stable. In this situation, the model exhibited a high goodness-of-fit, with an adjusted coefficient of determination (R^2) of 0.9454. The F-test of the model was highly significant, with an F-statistic of 104.8277 at the 0.1% significance level. All the estimated coefficients passed the significance tests with t-statistic at the 0.1% significance level. The VIFs of the estimated coefficients ranged from 0.1704 to 0.4791, all much lower than 10. The bias introduced was

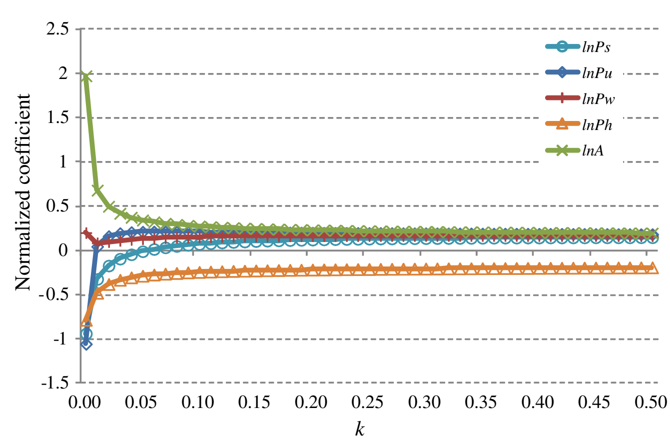

Fig. 2. Ridge trace estimated for Eq. (4).

Table 6
Ridge regression results of Eq. (4).

k				0.2000
Adjusted R^2				0.9454
Standard error				0.1067
F-statistic				104.8277***
Bias				0.0979
Variable	Non-normalized coefficient	Normalized coefficient	t-Statistic	VIF
lnPs	0.5543*** (0.1223)	0.1245	4.5329	0.4144
lnPu	0.3334*** (0.0350)	0.2029	9.5369	0.2486
lnPw	1.3210*** (0.2326)	0.1678	5.6796	0.4791
lnPh	−0.7823*** (0.0642)	−0.2146	−12.1808	0.1705
ln$A$	0.1646*** (0.0124)	0.2339	13.2784	0.1704
Constant	5.5205*** (1.4601)		3.7809	

Standard errors are in parentheses.
*** $p<0.001$ (two-tailed test).

0.0979, which is acceptable for the estimates. Thus, the estimation is considered satisfactory, with a robust explanatory power for Eq. (4).

5. Discussion

Table 6 lists the contributions of the impact factors on carbon emissions in terms of the absolute value of the normalized coefficients. The impact factors are ranked in descending order as follows: per capita expenditure, with a contribution ratio of 23.39%; household size, with 21.46%; urbanization rate, with 20.29%; proportion of working age population, with 16.78%; and population size, with 12.45%. On the basis of these results, we conclude that the effects of changes in residential consumption and population structure on carbon emissions in China over the studied period exceeded those of population size.

5.1. Residential consumption

According to the estimated equation, the impact of changes in per capita expenditure on carbon emissions in China was higher than that of the other factors considered in the model.

Table 1 and Fig. 1 illustrate that the residential consumption level in China maintained continuous growth from 1978 to 2008. In terms of the fixed prices in 2000, the per capita expenditure rose 8.17 times from CNY 740 to CNY 6782, with an annual average growth rate of 7.67%. This rate was higher than those of the other variables investigated.

As an important indicator of the affluence of residents, consumption level affects carbon emissions through two main channels. The first is through direct emissions from household energy requirements, including cooking, hot water use, and heating. The second is via indirect emissions from non-energy residential consumption goods and services, which emit carbon during, rather than after, the production process. The impacts of human behavior on carbon emissions are primarily manifested in production and consumption behaviors. This observation indicates that to satisfy consumption demands, people create wealth for society by participating in production activities, leading to inevitable emissions in a specific stage restricted to the level of productivity and resource endowment. In this sense, carbon emissions can be considered an indicator of social and economic development in a particular historical period. Hence, a high correlation between consumption level and carbon emissions is expected.

Nevertheless, the impact of changes in consumption structure on carbon emissions should not be disregarded. Marked by an increasing proportion of service consumption and a decreasing proportion of product consumption, China exhibited a significantly improved residential consumption pattern during the studied period (Wei et al., 2007). The relationship between consumption level and carbon emissions is not a simple linear correlation because the carbon emission intensity of each type of residential good or service differs, and the improvement in production technology and energy structure constantly varies. These factors partly explain the growth rate of carbon emissions being lower than the consumption level in China during the reviewed period, with the elasticity of per capita expenditure at only 0.16.

5.2. Population size

Table 1 and Fig. 1 show that from 1978 to 2008, the population increased from 0.963 billion to 1.328 billion, which is equivalent to an increase of 37.96%. The results of the Granger causality test (Table 4) suggest that the logarithmic variable of population size is the Granger cause of carbon emissions, with 83.81% significance. The regression estimation of the model shows that the elasticity of carbon emissions in relation to population size from 1978 to 2008 was 0.55. Compared with the similar global-level elasticities assessed by Shi (2003), Cole and Neumayer (2004), and Rosa et al. (2004), the impact of population size on carbon emissions in China during this period was considerably lower than the global average level, despite some differences among the variables and periods investigated in these studies. The lower impact of population size implies that during the period reviewed in the current work, population growth was not the major impact factor.

Population growth does not necessarily result in the inevitable intensification of environmental pressure. The consequences of population growth continue to be debated. In our opinion, the complexity of the relationship between population and the environment presents difficulties in resolving such controversial issues. First, a close mutual relationship exists between population growth and environmental pressure; i.e., population growth influences natural resources and the ecosystem, and vice versa. Second, these two factors usually interact with each other indirectly through human production and consumption behaviors, which are in turn influenced by social and economic factors, including productive relations, industrial policy, and resource endowment. Third, even population growth itself reflects different structural patterns, manifesting in varying age structures, gender compositions, and geographical distributions. Thus, comprehensively investigating the effects of the changes in population structure, rather than only those in population size, is necessary. Such studies should also include an analysis of the social and economic factors that affect environmental pressure. The next section describes these issues in detail.

5.3. Urbanization

Our results reveal that the urbanization of the population was key to the increase in carbon emissions in China, with an urbanization elasticity of 0.33.

As shown in Table 1 and Fig. 1, the urbanization rate of China's population rose from 17.92% to 45.68% in 1978 to 2008, with a yearly average increase of nearly one percentage point. A significant disparity in production and consumption levels exists between urban and rural areas because of the specialized urban–rural dualistic structure of China. Statistics show that for nearly a decade, the per capita expenditure of urban residents remained 3.5 times higher than that of rural residents. The rising urbanization rate primarily reflects improving production and consumption levels; urban residents would have been responsible for the large impact on the carbon emissions in China during the studied period.

Nevertheless, urbanization partly alleviates environmental pressure. Through intensive development, urbanization can improve energy use efficiency and pollution treatment through assembly and scale effects. These effects, in turn, mitigate the scarcity of energy resources and damage to the environment. According to the estimated urbanization rate elasticity, the carbon emission-promoting effect of urbanization in China in the last three decades was considerably higher than its alleviative effect.

5.4. Age structure

Our research shows that changes in population age structure visibly influenced the carbon emissions in China during the reviewed period, with the elasticity of working age population proportion being 0.33.

Changes in population age structure exert an indirect effect on carbon emissions, mainly by influencing production and consumption patterns. In terms of production, the continuous increase in labor force drove the rapid economic growth of China. The high correlation between carbon emissions and economic growth in the country partly explains the impact of the changes in age structure on emissions.

With respect to consumption, the mechanism of influence of changes in age structure remains complicated. From a micro perspective and according to the life cycle hypothesis (Modigliani and Brumberg, 1954), people optimally allocate their expected total lifetime income to different stages of lifetime to maximize inter-temporal utility. Hence, the growth in the proportion of labor force in a population would result in an increased total savings rate and lower total consumption rate. From a macro perspective, Dalton et al. (2008) found that an aging population would present inhibitory effects on carbon emissions in the long run. Given that working age population continues to increase and the capital stock allocated for each person remains fixed, part of consumption would be transformed to investments, resulting in decreased per capita consumption.

Table 1 and Fig. 1 demonstrate that the proportion of working age population in China rose by 13.3 percentage points, from 59.5% to 72.8% over 1978–2008. Meanwhile, statistics show that the proportion of the aging population significantly increased during this period, while that of children decreased. In terms of production and consumption, the aging population may have exerted some inhibitory effects on consumption and associated emissions; the adequate labor supply primarily accounted for the impact of change in age structure on carbon emissions in China in the last three decades.

5.5. Household size

The results of our estimated model show that shrinking household size significantly influenced carbon emissions in China during the reviewed period, with household size elasticity being −0.78.

The average household size in China from 1978 to 2008 continued to shrink from 4.66 persons to 3.16 persons, a decrease of 32.24% (Table 1 and Fig. 1). By approximate calculation, the total number of households increased by 1.04, which is much higher than the growth rate of population size in China during the studied period. Given that the consumption demand based on households includes numerous shared goods and services, the reduction in household size indicates the weakness of the scale effect on household consumption, resulting in the increase in per capita consumption. Meanwhile, given a steady growing population, the reduction in household size will lead to a faster increase in the total number of households, causing the increase in household-based consumption demand to exceed that in individual-based demand. These factors explain why our estimate of the absolute value of household size is larger than that of population size. It also implies that households, rather than individuals, are a more reasonable explanation for the demographic impact on emissions.

6. Conclusion and policy implications

Expanding the STIRPAT model and using the ridge regression method, we examined the impacts of population size, population structure, and consumption level on carbon emissions in China from 1978 to 2008. We used the ridge regression method to rectify the negative influence of multicollinearity among the independent variables under acceptable bias. Changes in consumption level and population structure were the two major factors that affected carbon emissions, not population size.

China has long emphasized energy conservation and emission reduction in industrial fields. Residential consumption rates have continued to decline in recent decades. Thus, the effect of residential consumption on carbon emissions seems unimportant. However, our study shows that the impact of changes in consumption level on carbon emissions in China was higher than those of the other factors considered in the model. With the implementation of policies for stimulating domestic demand as a way of coping with the international financial crisis, the impact of residential consumption on carbon emissions in China may significantly increase in the future. Therefore, policymakers should find a way to control emissions without sacrificing standards of living. As previously stated, the relationship between consumption level and carbon emissions is not a simple linear correlation; this relationship is influenced by consumption structure, production technology, and energy structure, creating an opportunity for gradually decoupling the synchronism between the growing consumption level and increasing carbon emissions in China in the future.

Considering that the natural growth rate of the population in China has continued to decline for more than 30 years, a policy that more aggressively reduces population size is no longer feasible. Given its substantial population base, however, China has seen a yearly increase in average population of more than 7 million since the beginning of this century; the population will continue to increase by about 100 million in the next two decades (Peng, 2011). The elasticity of emissions in relation to population size (as estimated in our model) was maintained; thus, carbon emissions in China will continue on a growth trend for the next two decades. Our study reveals that changes in population structure played a more important role than did those in population size. Therefore, policies that respond to changes in urbanization level, age structure, and household size should be seriously considered.

The overall demographic urbanization level in the country currently remains lower than the global average level, and it has not matched the corresponding level of industrial development. We can therefore expect China to continue to undergo urbanization in the next several decades, and the pressure of emission increase to grow stronger and last longer. In the last three decades, the principle underlying China's urbanization policy has changed from “control the scale of large cities, rationally develop medium cities, and actively develop small towns” to “develop large, medium, and small cities in a synchronized manner and form city groups with large radiation effects.” This conversion reflects the awareness of the vital function of concentrating the use of resources and environmental treatment in large-scale or medium-scale cities. Policymakers should more strongly emphasize the assembly and scale effects of cities to reduce emissions and initiate low carbon development.

The proportion of working age population in China peaked around 2010, indicating that the window of opportunity for the country's “demographic bonus” is in its closing process, and that the trend of population aging will be the major characteristic of China's age structure in the future. Given this backdrop, our results imply that changes in age structure will present an alleviation-dominant impact on carbon emissions in the future. This impact will significantly differ from the influence of age structure in the last three decades, which was characterized by an adequate supply of labor force. This preliminary evaluation promotes cautious optimism regarding the future trends of residential carbon emissions in China.

The reduction trend of household size was accompanied by social and economic development partly because of the implementation of the family planning policy in the country and the influence of urbanization on rural families. With modernization and urbanization, China's household size will continue to decrease, and using households in explaining the impact on carbon emissions will be an even more effective approach.

Thus, policies regarding residential consumption will extensively influence carbon emission trends. Policymakers should immediately initiate overall planning for population development and residential consumption by establishing the necessary assessment frameworks and guidance systems that promote low carbon development in China.

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