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# Forecasting Turning Points of Carbon Emissions in Beijing Based on Interpretable Machine Learning

**Tianen Yao, Yaqi Wang, Xinhao Li, Xinyao Lian and Jing Li ***

Institute of Child and Adolescent Health, School of Public Health, Peking University, Beijing 100871, China; txy112@alumni.bham.ac.uk (T.Y.); 2211110227@bjmu.edu.cn (Y.W.); xl498@cantab.ac.uk (X.L.); 1810306227@pku.edu.cn (X.L.)
* Correspondence: jing.li@hsc.pku.edu.cn

**Abstract:** For curbing the global climate crisis, China has set an ambitious target of peak carbon emissions by 2030. Beijing, the capital of China, has implemented a carbon reduction policy since 2012. Using the reduced and generalized forms of the Environmental Kuznets Curve (EKC), we deduce that both the cubic EKC and the genetic algorithm-based EKC have an N-shape. The first turning point of the three-order EKC occurs around 2011, demonstrating the effectiveness of the carbon reduction policy. However, the time series model predicts that Beijing will reach the second turning point around 2026, when the gross domestic product (GDP) is about CNY 5000 billion and carbon emissions will begin to increase again. Interpretable machine learning is proposed to explore the socio-economic drivers in carbon emissions, indicating that total energy consumption and GDP contribute the most. Therefore, we should accelerate the upgrading of energy consumption and adjust the industrial structure, thus facilitating Beijing to its peak carbon emissions and achieving carbon neutrality.

**Keywords:** Environmental Kuznets Curve; feature selecting; error correction model

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## 1. Introduction

Global warming is intensifying worldwide, followed by rising sea levels leading to shrinking land masses, and extreme weather threatening the survival of mankind [1,2]. The Beijing Air Pollution Control Measures 2012–2020 were released in 2012, opening the way for industrial structure reconstruction and environmental protection [3]. In the same year, Beijing was also included in the second batch of national low-carbon pilot cities, and continued to carry out two rounds of large-scale greening construction, mainly "164737 acres of afforestation", which has been given priority to optimizing Beijing's green ecological spatial pattern. Since the signing of the Paris Agreement and the Kyoto Protocol, China, as a major carbon emitter and developing country, has been making efforts to promote the implementation of carbon reduction in the country. Beijing, as the capital of China, naturally plays an exemplary leading role in achieving outstanding results in terms of total carbon emission changes and carbon emission intensity, and insists on giving priority to transforming the economic development mode and continuously improving the sustainable development level [4]. Therefore, there is an urgent need to determine when Beijing's carbon emissions will peak and whether it will be able to meet the 2030 target for the carbon emission peak. It is also essential to explore the drivers of carbon emissions in order to curb carbon emissions and promote carbon neutrality.

Grossman and Krueger [5] first introduced the Environmental Kuznets Curve (EKC) to describe the relationship between environmental quality and economic growth, and classified the impact of economic growth on environmental quality into three categories: scale effect, structural effect, and technological progress effect. Villanthenkodath et al. [6] inferred that as a country's population increased, the demand for energy consumption would also increase significantly, especially for fossil fuels such as coal, oil and gas. Dogan and Inglesi [7] deduced that the EKC hypothesis was not confirmed when using the share of industry to reflect the structure of European countries' economies. Brock and Taylor [8] detected that three different factors, such as technological progress, determined whether economic growth and environmental quality, followed linear, U-shaped or inverted U-shaped relationships. There is also an inverted U-shaped relationship between carbon emissions and economic growth through the EKC hypothesis by other studies, for example, globally [9], in EU member states [10], in OECD countries [11] and in 17 African countries [12]. William et al. [13] discovered that there existed an inverted U-shaped relationship for environmental pollution and economic growth. The first study by Lin et al. [14] found that overall economic growth was a key factor in the inverted U-shaped relationship exhibited by carbon ($CO_2$) emissions in the countries studied. However, an increasing number of studies have confirmed that N-forms [15] and inverted N-forms are also possible in EKC. For example, Wanger [16] and others proved $CO_2$ emissions and income existed an N-shaped relationship. Omri [17] studied the economies of Egypt, Iran, Saudi Arabia, Syria and several other countries where carbon emissions and economic growth were monotonically correlated. In other words, carbon emissions increased as the scale of production (measured by Gross Domestic Product (GDP) growth) increased, holding the composition of inputs and technology constant. Xu [18] analyzed that the EKC of carbon emissions in China was mainly due to technological progress and capital deepening, and that the effects of both factors were in an inverted U-shaped EKC [19]. Liu et al. [20] concluded that the theoretical turning point of EKC of China's carbon emissions was around 2020; furthermore, the EKC of carbon emissions was also influenced by energy intensity, industrial structure and technological changes [21], thus they concluded that the analysis of a simple EKC was not sufficient to describe China's carbon emissions.

However, there is a paucity of EKC coupled with time series to predict carbon inflection points and profile the socio-economic drivers of carbon emissions using interpretable machine learning. Our research objectives are (1) to determine whether a carbon emissions inflection point exists using EKC, and if the inflection point exists, to predict GDP through time series and thus the moment when carbon peaks; (2) the form of the multivariate EKC is ambiguous and several feature engineering algorithms are compared to select the optimal form of the EKC; (3) interpretable machine learning can be employed to quantify the socio-economic drivers of carbon emissions; (4) to investigate the long- and short-term relationship between carbon emissions and GDP with an error correction model (ECM), and (5) to assess the effectiveness of carbon reduction policies in 2012.

## 2. Methodology

The data in this paper are mainly based on the Beijing Statistical Yearbook 2021 (https://nj.tjj.beijing.gov.cn/nj/main/2021-tjnj/zk/indexch.htm, accessed on 19 October 2022), and the official website of the Beijing Municipal Bureau of Statistics (http://tjj.beijing.gov.cn, accessed on 8 November 2022), which are collected from 1978 to 2021. A multiple interpolation technique is used to fill in the missing values, and the processed data are shown in Figure 1, which presents that Beijing's GDP has experienced exponential and explosive growth since the reform and opening up. Carbon emissions, on the other hand, have risen and then fallen, suggesting that their relationship is non-linear. Other potential influencing factors include unemployment rates (UR), average temperatures (AT), sulfur dioxide ($SO_2$), life expectancy (LE), total energy consumption (Energy), exports, imports and population growth rates (RPG). DV denotes the dummy variables.

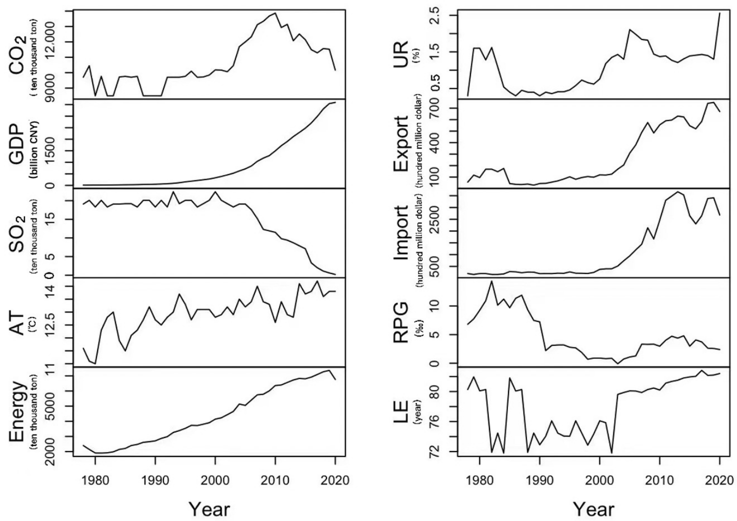


**Figure 1.** Data summary of time series in Beijing.

### 2.1. EKC Estimate

According to the EKC assumptions, once an economy has reached a sufficient level of economic growth, further economic growth can ameliorate environmental degradation. In the early stages of economic growth, when primary production dominates, natural resource reserves are abundant and waste generation is limited due to limited economic production activities. In the process of development through industrialization, the consumption of natural resources and the generation of waste are crucial. During this period, the relationship between income and environmental degradation was positive. As economic growth progressed, services, technological improvements and information diffusion reduced the material base of the economy, leading to a decrease in environmental degradation [22]. Moreover, with the depth of research, many scholars have found that the relationship between environmental quality and income is not only an inverted U-shape, but can also be a positive U-shape, N-shape and inverted N-shape. The ordinary and generalized forms of the EKC are shown below.

$$CO_2 = \beta_0 + \beta_1 GDP + \beta_2 GDP^2 + \beta_3 GDP^3 + e \tag{1}$$

$$CO_2 = \beta_0 + \beta_1 GDP + \beta_2 GDP^2 + \beta_3 GDP^3 + \sum_{i=4}^{11} \beta_i z + e \tag{2}$$

where $CO_2$ denotes carbon dioxide emissions, $z$ reveals other eight potentially variables that may affect economic growth and environment equality, and $e$ devotes the error term. The shape of EKC and the linkage of economic development and environmental quality are as follows. (1) When $\beta_1 = \beta_2 = \beta_3$, GDP and $CO_2$ are unrelated; (2) $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$ reveals that there exists a monotonically increasing linear relationship between GDP and $CO_2$ with no evidence of a turning point; (3) $\beta_1 < 0$ and $\beta_2 = \beta_3 = 0$ shows a monotonically decreasing relationship; (4) $\beta_1 > 0, \beta_2 < 0$ and $\beta_3 = 0$ represent that there exists an inverted U relationship between GDP and $CO_2$; (5) $\beta_1 > 0, \beta_2 < 0$ and $\beta_3 > 0$ illustrate an N-shaped relationship; and (6) $\beta_1 < 0, \beta_2 > 0$ and $\beta_3 < 0$ shows an inverted N-shaped relationship. Only cases (4), (5) and (6) indicate turning points which support the EKC. The inflection point of the second-order EKC is calculated by $-\frac{\beta_2}{2\beta_1}$. The calculation of the third-order EKC turning point follows a similar approach.

### 2.2. Machine Learning Algorithms

Machine learning algorithms are widely used in various fields of scientific research, of which feature engineering, also known as attribute selection, is roughly classified into three major categories: filtering, wrapping and embedding. It mainly refers to constructing models with good stability and generalization performance by mining effective information from raw data on a large scale and reducing dimensional catastrophes. The genetic algorithm was developed by John Holland in 1975 [23], and is one of the most popular metaheuristic approaches [24]. The root node of the decision tree usually refers to the most significant index, with great predictive performance and feature extraction ability (Xiaonuo et al., 2022). Nicole et al. [25] deduced that the filter approach had lower computational complexity and could sort the features. With a stepwise regression, the features can be selected at random at the start and then run a number of times to select the best features.

One of the biggest drawbacks of machine learning is insufficient interpretation; therefore, interpretable machine learning models have emerged, namely the Shapley additive explanation (SHAP) model. The SHAP approach is a "model interpretation" package developed in Python that can interpret the output of any machine learning model. Inspired by cooperative game theory, the SHAP technique constructs an additive explanatory model in which all features are considered "contributors". For each prediction sample, the model generates a prediction value, and the SHAP value is the value assigned to each feature in that sample. To explain the model in SHAP, we need to create an explainer. SHAP supports many types of explainers, such as deep, gradient, kernel, tree, sampling, etc. Extreme Gradient Boosting (XGBoost) is essentially a Gradient Boosting Decision Tree, which has the advantages of big data parallel computation and effective processing of sparse data, but it also lacks interpretability [26]. It is, therefore, necessary to construct a comprehensive explanatory framework, i.e., the SHAP−XGBoost algorithm could have high accuracy and interpretability. The SHAP value of each feature is:

$$s_i = s_{base} + f(X_{i1}) + f(X_{i2}) + \cdots + f(X_{ik}) \tag{3}$$

where the $i$th sample denotes $X_i$, the $j$th feature of the $i$th sample is $X_{ij}$, the predicted value of the model for this sample is $s_i$, and the baseline of the entire model (usually the mean of the target variables of all samples) is $s_{base}$.

### *2.3. Error Correction Model*

When non-stationary series meet the same order single integer, we usually use the cointegration test to study the non-stationary series after a certain linear combination of the series presents smoothness; additionally, the ECM can be exploited for investigating the short-term fluctuations. The ECM is often used after the cointegration test, as a complementary model of cointegration model. The Johansen cointegration test is carried out by calculating the maximum eigenvalue statistic and the trace statistic. The initial hypothesis of the Johansen cointegration test is $H_o$: $r_o \leq r$; $H_1$: $r_o > r$, where $r$ is the rank of the cointegrating vector.

The cointegration model can describe the long-term relationship between series, while the ECM can describe the short-run relationship between series. Suppose that there is a long-term equilibrium relationship between two series, namely $CO_{2t}$ and $GDP_t$. In other words, this is a cointegration relationship:

$$CO_{2t} = a_o + a_1 GDP_t + \mu_t \tag{4}$$

where $t$ presents the time series. If the series is non-stationary, the stochastic term $\mu_t$, also known as the long-run equilibrium error, or the disequilibrium error term, is used as the independent variable in the ECM. After a cointegration test, the error correction term is used as an explanatory variable, along with other explanatory variables that reflect short-term fluctuations, to create a short-term model, which is also an ECM.

$$\Delta CO_{2t} = b_o + b_1 \Delta GDP_t + \gamma ecm_{t-1} + \mu_t \tag{5}$$

where $\Delta CO_{2t}$ and $\Delta GDP_t$ are the results of the difference, $ecm_{t-1}$ reveals the term of error correction model, $t$ denotes the time series, and $\gamma$ reflects the strength of the adjustment when short-term fluctuations deviate from long-term equilibrium.

## 3. Results and Discussion

### *3.1. Prediction of Carbon Emissions Turning Points*

Using the second-order EKC estimate, the significance of each variable is strong. $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 = 0$, presenting an inverted U-shaped EKC, prove that there is a turning point for carbon dioxide emissions in Beijing. It is calculated that the GDP at the turning point is CNY 19,831 hundred million, which means that the carbon dioxide emissions in Beijing reached the turning point around 2012; before that, the carbon dioxide emissions increased with the economic development, but after that, the carbon dioxide emissions showed a decreasing trend with the economic growth and technological progress. More importantly, it was also in line with Beijing's carbon emission reduction policy in 2012.

When it comes to estimating the third-order EKC, the significance of all variables remains strong, where $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 > 0$, indicating that the relationship between $CO_2$ emissions and GDP shows an N-shape and its turning point exists. In addition, the coefficient of determination of the cubic EKC estimate is higher than that of the second-order EKC estimate. The two turning point values are calculated to be about CNY 16,528.67 and 48,089.34 hundred million. The first turning point occurred around 2011 and seems to be consistent with the quadratic EKC to some extent, while the other can be predicted by some time series models.

For the second turning point, easy evidence exists for future moments, therefore, this paper uses a differentially integrated moving average autoregressive model ($ARIMA(p, d, q)$) for GDP forecasting, where $d$ is the order of difference that makes it a smooth series, and $q$ is the sliding average. The fundamental principle is a model built after transforming the data into a smooth series by differencing and then regressing the dependent variable on only its subsequent terms and the present and lagged values of the random error terms. ARIMA prediction of GDP supports the forecast of Beijing's carbon turning point.

The model selected is the $ARIMA(0, 2, 2)$ model as shown in Figure 2. Furthermore, the model passes the Ljung-Box test with a $p$-value of 0.6541, which is greater than 0.05, hence the residual series is white noise [27]. This mainly means that the model explains the original series well. For the GDP predicted by the ARIMA approach, it is expected to reach CNY 48,718.24 hundred million in 2025, hence it is inferred that the second theoretical turning point of carbon emissions will occur in 2025. Then we will witness an increase in carbon emissions in Beijing. Therefore, we can investigate the EKC extended form, and delay the next turning point by export reduction and many more methods.

When it comes to multivariate EKC modified by machine learning, Table 1 demonstrates that there exist turning points for EKC based on a genetic algorithm and a stepwise regression, with N-shaped and inverted N-shaped curves. The calculated turning points for the genetic algorithm are CNY 3829.25 and 52,561.24 hundred million, and this means that carbon emissions started to fall around 2000, then are expected to start rising again in 2027. As for the EKC based on a stepwise regression, it indicates that the first turning points existed in 2001. Moreover, $CO_2$ emissions began to increase this year, and are projected to fall in 2035 when GDP is about CNY 7000 billion. The former is more convincing because it has the same shape as the third-order EKC, and Beijing is experiencing a decline in carbon emissions.

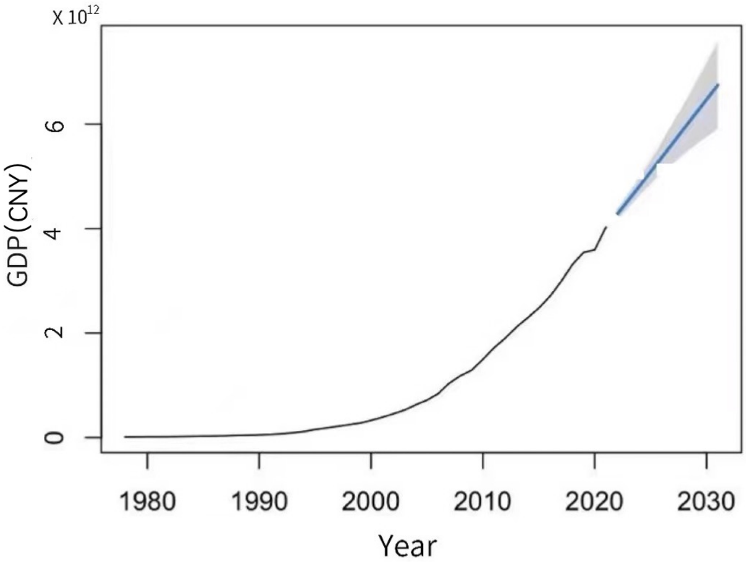


**Figure 2.** ARIMA(0,2,2) model forecasting diagram of Beijing GDP. The grey area indicates the interval of Beijing's GDP forecast, and the blue line indicates the mean value of Beijing's GDP forecast.

**Table 1.** EKC reduced forms and generalized forms based on machine learning algorithms for Beijing.

| Models | Square EKC | Cubic EKC | Generalized EKC | Filter Method | Decision Tree | Stepwise Regression | Genetic Algorithm |
|---|---|---|---|---|---|---|---|
| Intercept | 9145 *** | 8945 *** | −1777 | −2014 | −6336 * | −1160 | 11,160 *** |
| GDP | 0.3954 *** | 0.5587 *** | −0.0300 | −0.4035 * | −0.3247 | −0.0447 | 0.6581 ** |
| $GDP^2/10^4$ | −0.0992 *** | −0.2271 *** | −0.0607 | 0.0603 | −0.0267 | −0.0710 | −0.3073 *** |
| $GDP^3/10^8$ | - | 0.0234 *** | −0.0080 | −0.0055 | −0.0011 | 0.0103 | 0.0363 ** |
| Energy | - | - | 1.111 * | 1.8500 *** | 1.5060 *** | 1.1390 * | −0.1844 |
| Export | - | - | 8.8220 *** | 6.7090 *** | 6.3260 *** | 8.4720 ** | - |
| Import | - | - | −0.8701 *** | −0.5000 * | −0.3312 | −0.8234 ** | - |
| UR | - | - | −612.6 * | - | - | −582.7 ** | - |
| AT | - | - | −250.8 | −290.9 | - | −245.4 | - |
| $SO_2$ | - | - | 37.39 | 8.024 | 0.3374 | - | −90.87 |
| RPG | - | - | 69.81 | 110.5 ** | 87.82 * | 67.19 | - |
| LE | - | - | 130.3 *** | 116.4 *** | 141.1 *** | 130.2 *** | - |
| $R^2$ | 0.8255 | 0.8587 | 0.9685 | 0.9591 | 0.9544 | 0.9679 | 0.8653 |

It is noted that "***", "**", "*" and "." are indicated as significant at the 0.1%, 1%, 5% and 10% levels, respectively. "-" indicates that relevant variables are not being considered.

### 3.2. Influencing Factors of Carbon Emissions

The generalized form of the EKC is then used to examine all the potential variables. From the values of the coefficients of determination shown in Table 1, the multivariate EKC estimates fit better than the reduced forms of EKC, but several variables are not significant or there are no turning points, indicating the existence of redundant features; hence, this paper focuses on introducing the algorithm of machine learning for many feature selection models to select the optimal features. Although the coefficient of determination of stepwise regression is slightly lower than the original extended EKC formula, it is higher than other feature screening algorithms. In addition, stepwise regression excludes $SO_2$ emissions, demonstrating that there is an inflection point in carbon emissions, which improves the original EKC estimate.

Overall, the multiple regression equations based on all four machine learning feature selection algorithms are considered valid with p-values tending towards 0. However, the goodness-of-fit is slightly lower than before feature filtering, suggesting that there are other potential factors influencing the generalized form of the EKC. Compared to the third-order

EKC form, the generalized forms are more remarkable. This mainly means that the study of multiple EKC forms makes a difference.

SHAP−XGBoost is implemented to investigate the extent to which each indicator affects carbon emissions. It also shows that both anthropogenic and economic impacts are primary, especially human activities. Total energy consumption and life expectancy are the most influential variables, followed by GDP. On the contrary, imports are at the bottom of the list, suggesting that they have little impact on Beijing's carbon emissions. From Figures 3 and 4, GDP initially encourages carbon emissions but, as GDP increases, it becomes negatively correlated with carbon dioxide emissions. This is consistent with the conclusion of the simplified form of the EKC. Moreover, the trend of the impact of the total energy consumption on carbon emissions is the same as that of the GDP, which gradually increases and then decreases.

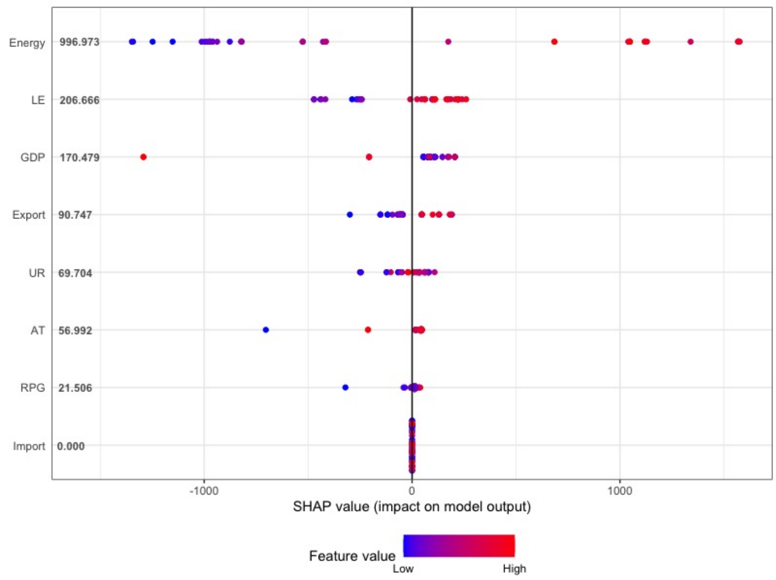


**Figure 3.** Feature contribution ranking by SHAP−XGBoost model.

### 3.3. Results of Error Correction Model

The time series plots of $CO_2$ emissions and GDP in Beijing are shown in Figure 1. Overall, Beijing's GDP has gradually increased with capital accumulation and technological progress, and experienced high growth rates in the early part of the twentieth century. Thanks to the implementation of low carbon economy policies, $CO_2$ emissions increased and then gradually decreased.

According to the unit root test (ADF), both $CO_2$ emissions and Beijing's GDP are non-stationary. The non-stationary series are then differenced, and the test shows that the differenced carbon emissions and GDP both pass the ADF test and are second-order single integers that satisfy the homogeneous single integer condition. The results show that there is a cointegration effect in the relationship between carbon emissions and GDP, indicating that the regression relationship expressed in the regression equation of carbon emissions and GDP is not a pseudo-regression, and the next step can be performed in the error correction model. In accordance with the Schwarz criterion, the optimal lag term is of the third order.

$$\Delta CO_2 = 93.455 - 0.4272 * ect1 - 0.1681 * \Delta GDP_{t-1} - 0.6303 * \Delta GDP_{t-2} \quad (6)$$

where $ect1$ denotes the residual difference term obtained in the cointegration regression test, which represents the value of the error in the previous period. In the model for carbon emissions and GDP, the value of the error term coefficient is −0.4272, implying that when the short-term fluctuations deviate from the long-term equilibrium, the disequilibrium will be pulled back to equilibrium with an adjustment of −0.4272 (42.72%).

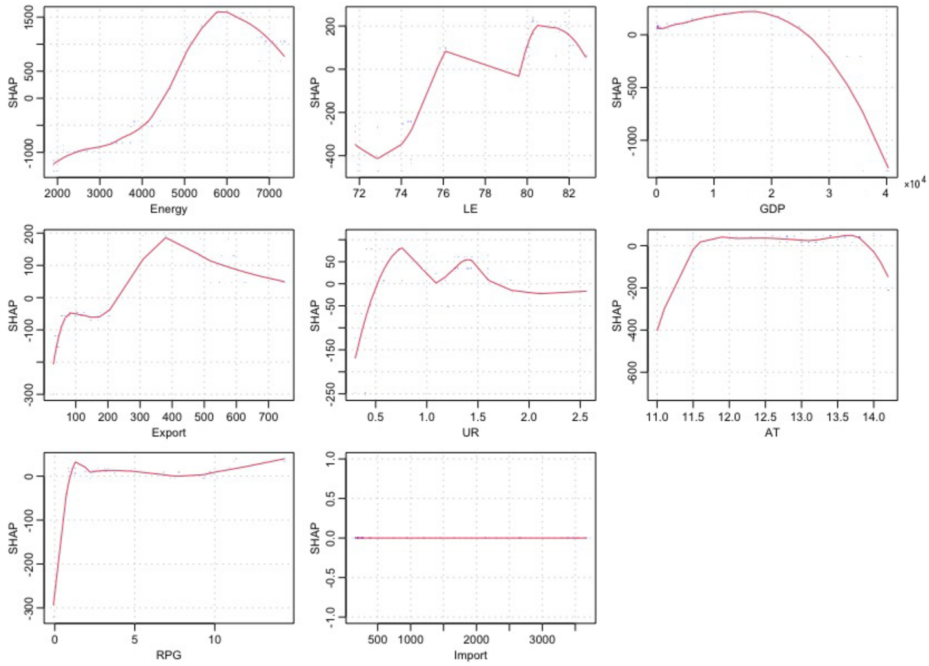


**Figure 4.** The relationships between each index and carbon emissions based on SHAP values.

### 3.4. Low-Carbon Policy Analysis

The above results show that one of the turning points is 2012, which is in line with the expectation of Beijing's strategy. Therefore, we can add a dummy variable in the generalized EKC model; more specifically, 0 can be added before 2012, while 1 can be added after 2012.

Table 2 shows that the p-value of the dummy variable is less than 0.05, indicating that Beijing's carbon emission reduction policy in 2012 played a significant role in carbon emission. The value of the regression coefficient is −878.5, which means that the implementation of the carbon emission reduction policy reduces carbon emissions by 8.785 million tonnes, compared to no implementation of the carbon emission reduction policy.

**Table 2.** EKC generalized model combining with dummy variable.

| Variables | Coefficients | Standard Variance |
|---|---|---|
| Intercept | −2902 | 2845 |
| GDP | −0.067 | 0.1883 |
| $GDP^2/10^4$ | −0.01273 | 0.07643 |
| $GDP^3/10^8$ | −0.005478 | 0.01102 |
| LE | 131.1 | 21.85 *** |
| AT | −224 | 127.3 |
| $SO_2$ | 77.22 | 49.72 |
| Export | 8.573 | 1.251 *** |
| Import | −0.9289 | 0.2266 *** |
| Energy | 1.107 | 0.4074 * |
| RPG | 70.7 | 35.47 |
| UR | −592.1 | 188.6 ** |
| DV | −878.5 | 470.2 * |
| $R^2$ = 0.9726 | $R^2_{adj}$ = 0.962 | |

It is noted that "***", "**", "*" and "." are indicated as significant at the 0.1%, 1%, 5% and 10% levels, respectively.

### 3.5. Limitation of Our Study

Current research on the generalized form of the EKC is immature, hence we collected as many typical enough factors as possible and introduced some machine learning feature screening algorithms to determine its specific form. In terms of the optimal features retained by the various algorithms, it is straightforward to note that the fit tends to increase slightly as the number of features increases, suggesting that there are still other potential influence factors to be discovered. For example, education level and the number of cars, which are taken into account in the generalized EKC model in some scholars' studies. However, we do not include them in this paper due to data limitations; therefore, we can consider more potential influences to optimize the model in subsequent studies. In the EKC study of $CO_2$, sulfur dioxide emissions are controversial, partly due to insufficient data. In addition, the best feature filtering algorithm in this paper is the genetic algorithm, but there are still more feature selection algorithms with a higher computational efficiency, such as the particle swarm optimization algorithm, simulated annealing algorithm, support vector machine (SVM) algorithm, and neural network algorithm, which can be combined with the generalized form of EKC to further improve the performance of the model.

## 4. Conclusions

Our investigation aims to examine the relationship between GDP growth and $CO_2$ emissions in Beijing and the theoretical turning point of carbon emissions. The results of the EKC suggest that the relationship between GDP growth and $CO_2$ emissions is not a pseudo-regression, and that there is a short-term fluctuating relationship. Our study compares the generalized form of the EKC and uses its simplified form as a cornerstone. The calculated turning points of Beijing's inverted U-shaped or N-shaped EKCs are reconciled with Beijing's low-carbon policies. The extended form of the EKC, which includes nine relevant factors, can be optimized by various feature engineering algorithms. In comparison, the genetic algorithm outperforms the generalized form of the EKC. The results show that the point at which carbon emissions start to rise again in 2027 is delayed by two years from the EKC's reduced form, due to multiple factors. Based on the SHAP values, total energy consumption, life expectancy per capita and GDP also contribute significantly to Beijing's carbon emissions and therefore, a low-carbon energy transition and green economic development are imminent.

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**Data Availability Statement:** Data are available if requested.

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