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Study on the Coupled and Coordinated Development of Green Finance and Regional Economic Ecology

-- Anhui Province as an Example

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Abstract

The role of green finance in building local economic ecosystem is very obvious. This paper establishes a comprehensive index system of green finance and regional economic ecosystem systematization with 14 years of data from Anhui Province, and tries to analyze the relationship between green finance and local economy in Anhui through LightGBM model. The results conclude that the importance of characteristics such as investment in environmental infrastructure construction, fixed asset investment and local fiscal expenditure do not differ much, indicating that each method has almost the same degree of influence on the development of green finance.

Keywords

Green Finance; LightGBM Model; Coordinated Development.

1. Introduction

After the 19th Party Congress put forward the concept of green development, green development has become an important part of China's economic development and ecological civilization construction; finance is an important driving force for economic and social development, and green development needs the support of green finance. Green economy needs strong support from green finance to stimulate more potential and growth potential. For Anhui, which has a good ecological environment but an underdeveloped economy, the coordinated development of economy and ecology is the current focus and the future development path. In this paper, we take the harmonious development of green finance and local economy and ecology in Anhui Province as an example to study the relationship between the two and promote the harmonious development of green finance and ecology.

2. Review of the Literature

(i) There are aspects on green finance. Zhu Xiangdong et al.0 explored the impact of policy incentives, financial base and environmental pollution on green finance in 142 cities above prefecture level in China from 2016 to 2019 using a panel data model and a spatial Dobbin model. The study shows that there are regional differences in the development patterns of green finance. The eastern region is a homeopathic transition driven by policy incentives and financial base, while the central and western regions need to deal with the resistance brought by environmental pollution. Zuo Zhenglong[2] proposed that under the guidance of the concept of integrated urban and rural development, the focus should be on developing carbon finance derivatives based on forest deduction projects, creating an efficient carbon finance market, cooperating with the circulation of carbon finance instruments, and building a perfect carbon finance legal system to ensure the normal operation of carbon finance. Zhang Xiao Ke et al.[3]

introduced green credit policy in 2012 as a quasi-natural experiment to study the dual optimization effect of green credit policy on resource allocation efficiency between heavy and light polluting industries and within heavy polluting industries. (ii) There are aspects on regional economic ecologization. Yin Ana et al.[4] constructed a dynamic panel model to specifically study the different effects of environmental governance on the economic ecological development of Beijing-Tianjin-Hebei. The results show that from 2004 to 2017, command-and-control environmental regulation has a significant negative impact on the economic and ecological development of Beijing-Tianjin-Hebei, and the impact of economic incentives and voluntary environmental regulation on the economic and ecological development of Beijing-Tianjin-Hebei is characterized by an inverted "U"-shaped curve. Zhou, Cheng et al.[5] found that the regional economies and tourism systems of the provinces and cities along the Yangtze River Economic Belt were highly correlated, but there was no significant conflict between environmental protection and economic development. The degree of integration and coordination of the three systems is slightly higher if each provincial region is not counted in the next few years. Zhang Fuqing et al.[6] established an evaluation model and index system for regional ecological, economic and industrial linkages, and studied six districts and cities in the Poyang Lake Ecological Economic Zone from 2004 to 2008, especially the degree of coherence and discussed coherence, and empirically analyzed the internal structure of the hierarchy and industrial ecology.

3. Study Design

3.1. LightGBM Model Principle

LightGBM is a distributed framework for computing gradient-improved classification models to enhance the overall framework, one that uses the idea of combining the Histogram (Histogram) algorithm and the Leaf-wise fast growth (Leaf-wise) strategy layout limited by depth and breadth, while T weak regression trees are linearly combined into strong regression trees, as shown in equation (1). Subsequently implement how to classify or regress large data sets or small batch data samples.

$$F(x) = \sum_{T}^{t=1} f_t(x) \tag{1}$$

where F (x) is the final output value and f t(x) is the output value of the tth weak regression tree. For most decision tree algorithm models use a level-wise growth strategy layout, i.e., the leaf node positions at the same level are each approximately split into, but indeed some leaf nodes have a low direct split damage boost, so that not splitting adds a not insignificant additional overhead, as shown below.

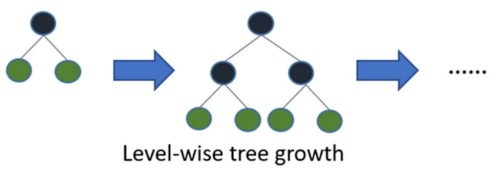

Figure 1. Leaf-wise strategy growth process

The leaf correlation strategy used by LightGBM is to find and decompose the leaf node 1 with the largest branch in the current leaf node every 3-5 times, but decomposing all nodes sets, in fact, and improves the accuracy not enough, as follows.

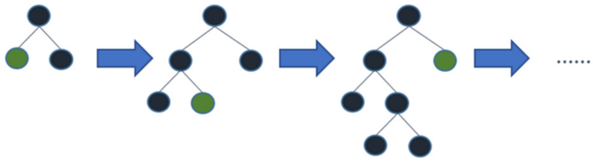

Figure 2. Leaf-wise strategy splitting gain

The bar graph algorithm, also called the bar graph algorithm procedure, simply means that the feature values are initially framed, which also means that the feature values of successive floating targets are extracted as an integer k to create a box (bins) and create a bar graph of breadth k. Once the information is traversed, the statistics within the bar graph are accumulated to support discrete values as indexes. The statistics accumulated within the bars support discrete values as the frequency bars accumulate the specified statistics once traversing the information once and then traversing the bars to search out the best partitioning purpose that supports the individual values of the bars.

3.2. LightGBM Hyperparametric Optimization

In the LightGBM model, there are several hyperparameters that need to be manually adjusted, such as the maximum tree depth, the minimum information gain for active crawling, and the number of leaf nodes per unit tree. The proper setting of these parameters determines the performance metrics such as the fit rate and accuracy of the model prediction results. The standard strategies for standardizing the parameters are random search and grid search. Grid search is a correlation-complete search technique with a set step size in which every purpose in the coordinate region is computed to search for the best parameters among the familiar ones. However, if the step size of the grid is not small enough, the optimal parameters in the grid search may also be removed from the optimal parameters; once the step size is small enough, the optimal parameters all over the world are found, however once the coordinate area is huge, it should lead to an excessive range of invalid computations, causing an exponential increase in computation time. Since the LightGBM model has multiple parameters and the parameter values are highly variable, a large range of computations is required if a grid is used to explore the parameters, so grid search is not applicable and random search is difficult to search for the global optimal resolution, so new strategies are needed to solve the problem of LightGBM hyperparameter optimization.

From Bayes' theorem (as shown in Equation (2)), the tactic uses familiar information to correct for previous chances and therefore calculates the posterior chances, while the entire valid historical analysis results will be used to improve the effectiveness of the search.

$$P(Y \mid D) = \frac{P(D \mid Y)P(Y)}{P(Y)} \tag{2}$$

where Y denotes the parameters of the parametric model; P(Y) denotes the prior probability model; D is the set of observed vectors; and P(Y|D) denotes the proxy of the objective function, obtained by the correction of the likelihood distribution P(D|Y). After each iteration, the probabilistic proxy model is updated, and the observed set D and the probabilistic proxy model are updated by maximizing the collection function, calculating new evaluation points, and passing them into the system again as inputs for iteration to obtain new outputs.

Among the parametric models, the common probabilistic models are GaussianProcesses and tree-structured Parson's estimators (TPEs), among which the mathematical process is highly flexible and quantifiable, so in this paper we choose the mathematical approach to model the agents in the multi-categorization formulation of the small-sample knowledge learning scheme, and the acquisition operation used to support the lifting strategy.

In the process of optimizing LightGBM hyperparameters using Bayes, several known points in the unknown function need to be selected as prior events, assuming that the selected points obey a multidimensional Gaussian distribution, and according to the Gaussian distribution formula, the mean and variance of each point can be calculated, i.e., the Gaussian process consists of a mean function with a semi-positive definite covariance function. Assuming that x is the input data set data, given the 2 parameters of the mean vector and covariance matrix, the parameter y will obey the joint normal distribution as shown in equation (3) in order to perform a recursive calculation of the relationship between the observations y_n and y_{n+1}.

$$\begin{bmatrix} y_1 \\ y_2 \\ M \\ y_n \end{bmatrix} \sim N\left(0, \begin{bmatrix} k(x_1,x_1),k(x_1,x_1),L,k(x_1,x_1) \\ k(x_2,x_1),k(x_2,x_2),L,k(x_2,x_n) \\ M \\ M \\ k(x_n,x_1),k(x_n,x_2),L,k(x_n,x_n) \end{bmatrix}\right) \tag{3}$$

If the covariance matrix (i.e., the kernel matrix) is denoted K, since Y obeys a multi-normal distribution, the optimal kernel matrix can be computed from the training set, which in turn leads to the posterior estimate test set Y^*. According to the relevant properties of the Gaussian process, the set of observed values y and the set of predicted function values y^* obey the xjoint distribution shown in equation (4) as follows.

$$\begin{bmatrix} y \\ y_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K & K_*^T \\ K_* & K_{**} \end{bmatrix}\right) \tag{4}$$

Of which. $K_* = \left[k(X_*,X_1),k(X_*,X_2),\dots,k(X_*,X_n)\right], K_{**} = k(X_*,X_*)$

The conditional distribution of the predicted data $p(y_* | y)$.y* can be found after calculating the joint distribution.

$$y_* | y \sim N\left(K_*K^{-1}y, K_{**} - K_*K^{-1}K_*^T\right)$$

Finally, the mean value is used as an estimate of the predicted data, as shown in equation (5).

$$\bar{y}^* = K^*K^{-1}y \tag{5}$$

4. Empirical Analysis

4.1. Establishment of Indicators

Based on domestic and foreign literature research, this paper creatively introduces indicators such as total investment in environmental protection, investment in environmental infrastructure construction, investment in fixed assets, local fiscal expenditure and total import and export to build a coupled and coordinated development indicator system from two dimensions of green finance and regional economic ecology, as shown in Table 1.

Table 1. Green finance and regional economic indicators system

Rating indicators	Level I indicators	Secondary indicators	variable	Indicator attributes	unit
Coordinated development	green finance	Total environmental investment	X_{11}	forward	billions
	Ecologization of the regional economy	Investment in environmental infrastructure development	X_{21}	forward	billions
		Fixed asset investment	X_{22}	forward	billions
		Local financial expenditures	X_{23}	forward	billions
		Total imports and exports	X_{24}	forward	billions
		Loans from banking financial institutions	X_{25}	forward	billions

4.2. Correlation Coefficient Analysis

With 14 years of regional economic and green financial data of Anhui Province, the correlation coefficient matrix R between variables is obtained through data processing, as shown in Table 2, it can be seen that there is a certain correlation between 6 main financial indicators, among which the correlation between industry financial institution loans and fixed asset investment is the strongest at 0.9938, which is due to the fact that industry financial institution loans are conducive to promoting more funds for market enterprises and lowering the cost of financing At the same time, the main source of fixed asset investment relies on loans from banks and other financial institutions, so the changes in loans from industry financial institutions and fixed asset investment show similarity; followed by fixed asset investment and local fiscal expenditure at 0.9866, indicating that the increase in local fiscal expenditure is conducive to increasing fixed asset investment, thus promoting economic development, and vice versa when fixed asset investment needs to increase on the contrary, it drives the increase of local fiscal expenditure.

Table 2. Table of correlation coefficients of variables

	Total environmental investment	Investment in environmental infrastructure development	Fixed asset investment	Local financial expenditures	Total imports and exports	Loans from banking financial institutions
Total environmental investment	1.0000	0.6104	0.5164	0.5371	0.5054	0.5111
Investment in environmental infrastructure development	0.6104	1.0000	0.9178	0.9519	0.9389	0.8857
Fixed asset investment	0.5164	0.9178	1.0000	0.9866	0.9659	0.9938
Local financial expenditures	0.5371	0.9519	0.9866	1.0000	0.9744	0.9750
Total imports and exports	0.5054	0.9389	0.9659	0.9744	1.0000	0.9566
Loans from banking financial institutions	0.5111	0.8857	0.9938	0.9750	0.9566	1.0000

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4.3. LightGBM Model Analysis

4.3.1. Model Building and Training

Reading 14 years of regional economic and green finance data in Anhui Province, the characteristic variables are investment in environmental infrastructure construction, fixed asset investment, local fiscal expenditure, total import and export, and loans from banking financial institutions, representing the level of regional economic development in these four areas (unit: billion yuan), and the target variable is total investment in environmental protection (unit: billion yuan).

After extracting the feature and target variables, the data is split into a training set and a test set with the following code.

```
fromsklearn.model_selectionimporttrain_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=123)
```

Once the training and test sets are delineated, the LightGBM regression model can be introduced for model training.

4.3.2. Model Prediction and Evaluation

After the model was built, the predictions were made on the test set data and the predicted and actual values were summarized for comparison, as shown in Table 3, where it can be seen that the predictions for the first 3 items are more accurate.

Table 3. Comparison of actual and predicted values

predicted value	actual value
739.3247	763.7359
398.6255	352.1579
183.5428	157.9000

In order to better predict environmental investment, we can filter out the characteristic variables that have a greater impact on green investment development by looking at the characteristic importance of each characteristic, and it turns out that the characteristic importance of environmental infrastructure construction investment, fixed asset investment, local fiscal expenditure, total imports and exports, and loans from banking financial institutions do not differ significantly, indicating that each approach affects green finance to nearly the same extent development.

4.3.3. Model Parameter Tuning

The parameters of the model built earlier are tuned using GridSearch network search with the following code:

```
fromsklearn.model_selectionimportGridSearchCV
parameters={'num_leaves':[15,31,62],'n_estimators':[20,30,50,70],'learning_rate':[0.1,0.2,0.3,
0.4]}
model=LGBMRegressor()
grid_search=GridSearchCV(model,parameters,scoring='r2',cv=5)
```

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In the following, the training set data is passed into the network search model and the optimal values of the parameters are output and the optimal values of the parameters obtained are as follows.

{'learning_rate':0.1,'n_estimators':20,'num_leaves':15}

That is, for the data in this paper, the model predicts best when the learning rate is set to 0.3, the maximum number of iterations is set to 50, and the maximum number of leaf nodes in the decision tree is set to 31.

5. Conclusion

This paper argues that green finance and local economic ecology will interact with and influence each other by combining the relevant literature on green finance and local economic ecology. By studying the relationship between green finance and regional economic ecosystem in Anhui and implementing related measures, the research on the relationship between green finance and regional economic ecology in Anhui Province will be better promoted.

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