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Analysis of Green Credit and the Ecological Welfare Performance Based on Empirical Models and ARIMA(2,3,2): Taking China as an Example

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Abstract: We study the relationship between green credit and ecological welfare performance, green credit’s mechanism, and future trends of ecological welfare performance in China. We aim to determine whether the green credit policy has a positive or negative effect on ecological welfare performance and to give suggestions about green credit for emerging markets, with China as an example. These problems are evaluated with two empirical models by using quadratic and interaction terms, as well as a time series model, ARIMA(2,3,2). The results show that the relationship between green credit and ecological welfare performance is an inverted U shape, and ecological welfare performance peaks when loans approach 2934.2 billion yuan, which equals 441.7446 billion dollars, corresponding to loans between 2015 and 2016. In addition, national income and ecological footprint have a suppressive effect on the impact of green credit on ecological welfare performance, and lifespan can positively affect the mechanism. Moreover, the result of ARIMA(2,3,2) corresponds to previous results and indicates that the ecological welfare performance will fluctuate within a range if green credits continue to be issued.

Keywords: ecological welfare performance; green credit; ARIMA; difference GMM

1. Introduction

The solutions to serious environmental problems for banks have been hotspots for years. In 1974, the Federal Republic of Germany established the world’s first policy bank for environmental protection, called the “Ecobank”, to provide preferential loans for environmental projects that banks would not usually accept. In 2003, 10 international banks, including Citibank, ABN-AMRO bank, Barclays bank, etc., announced that they had adopted the Equator Principles (EP), which are intended to identify, assess, and manage environmental and social risks for financial institutions. Green credit is a policy proposed in 2007 in China. It applies to commercial banks and other financial institutions that ease lending to companies in highly polluting or energy-intensive firms or projects.

Daly was the first who proposed to assess the sustainable development of countries by calculating the increase in the level of welfare per unit of natural consumption, corresponding to the concept of ecological welfare performance (EWP) [1]. After the ecological footprint (EF) was proposed, which indicates natural consumption, research on EWP was developed. Compared to indicators such as forest coverage, carbon dioxide emissions, etc., EWP is a multifaceted evaluation indicator, which includes social welfare and nature consumption. Our study will identify the relationship between EWP and green credit, investigate the change in EWP in the case of issuing enormous green credit based on past data, and discuss factors affecting the mechanism of green credit.

The model for evaluating the impact of green credit on sustainability performance for manufacturing, built by Nabeeh [2], shows that the green credit policy can provide more chances to attain sustainability in manufacturing. Zhang et al. found that the green credit
policy improved the environment in China overall, but the emission reduction effect is significant where there is a highly developed financial market [3]. Liu concluded that the green credit policy can effectively restrain the outputs of energy-intensive industries, but, still, the investment in the target industries will bounce back, which brings adverse effects on the economy [4]. However, lian et al. mentioned that green credit improves commercial banks’ financial performance [5]. Thus, many types of research on green credit policy only focus on one aspect. In addition, only a few people are currently studying EWP in China. The unanswered questions about the overall impact of green credit on society and factors affecting EWP remain.

Figure 1 shows the framework of EWP. Most researchers identify EF as ecological resource consumption. However, the indicator for social welfare has been debated. Dietz [6] defined EWP as the ratio of life expectancy at birth (LEB) to EF per capita. Zhu [7] quantified EWP by using the ratio of the human development index (HDI) to EF. HDI is a summary measure of average achievement in key dimensions of human development. It comprises three areas: access to education, LEB, and gross national income (GDP) [8]. There are direct data for LEB and GDP, but, because of nine-year compulsory education, a traditional method for assessing education is not suitable. Thus, in this paper, we construct a new assessment system for access to education by the entropy method. Furthermore, green credit, as one of the economic activities, will be studied in this paper for its impact on EWP.

As for factors affecting the mechanism of green credit, based on the above framework, we divide them into two categories, namely social welfare and ecological resource consumption, to explore their interactions.

The contributions are as follows:
1. We innovatively discuss the relationship between green credit and ecological welfare performance and their operation mechanism. Therefore, the evaluation criteria of green credit have been simplified from a system to an indicator. These criteria can be adopted to evaluate the performance of new financial derivatives.
2. We extend the trend prediction interval of ecological welfare performance to 10 years, which means that it is possible to research the long-term tendency of ecological welfare performance, especially in the emerging market.
3. The entropy approach instead of the traditional formula is firstly adopted to evaluate the performance of the annual education level.
4. The proposed model is efficient to perform ecological welfare performance forecasting, which is verified by experimental results.

This paper is composed of seven main sections. There is a literature review in Section 2. Following the literature review, Section 3 will show the data, and Section 4 will evaluate the EWP in China. Moreover, two econometric analyses and a time series analysis are
conducted to identify the relationship between green credit and EWP, factors affecting the mechanism of green credit, and the forecast of EWP in Section 4. In Section 5, we will explain the computational method. Section 6 presents the results of Section 3. In Section 7, we will give a conclusion.

2. Literature Review

The study of green credit in China often focuses on two aspects, the risks and its performance. The correlation between green credit and its risks depends critically on the size and structure of the company, which means that state-owned major banks can decrease their risks by applying this credit policy, but it is not suitable for small city/regional banks [9]. Moreover, Zhao proves this conclusion by studying the transmission mechanisms of green credit risk. We find that government intervention, green technology innovation, and regulatory authority behavior can influence the risk [10]. In addition to the uncertainty of the risk control for green credit, its contribution is also uncertain. A key insight from this literature is that there is a heterogeneity. For example, green innovation and green total factor productivity in places with a high degree of environmental regulation and economic development can be improved more by green credit [11–13]. However, Wang presented a contrasting view that the positive effect of green credit on innovation is more significant in less financially developed areas [14], and Wen even claimed that green credit has a negative effect on the research and development intensity and the total factor productivity of energy-intensive enterprises [15]. In addition, green credit can more strongly enhance the peer effect of environmentally friendly industries than high-pollution, high-energy-consumption, and overcapacity industries [16]. We also find that green credit guidelines have a significant effect on the green innovation of state-owned and large enterprises, but have little effect on the green innovation of non-state-owned and small ones [17,18]. In summary, researchers do not have a standard to judge green credit, or to evaluate it from multiple perspectives and at different levels. We now introduce the EWP in detail, which is a suitable indicator containing ecology and welfare levels for assessing its performance.

The main methods for calculating the EWP fall into two categories: EF and HDI. As a numerator and denominator, they are always used in previous studies at the country level, whereas others use multiple variables to construct an evaluation system at the province or city level by different models, such as the DEA and Malmquist index methods [19], as well as the two-stage super-efficiency slack-based model [20]. After calculating the EWP using either of the two methods, exploring the factors influencing EWP and its spatial visualization and evolution characteristics is also an active area of research. For factors influencing EWP, we find that the urbanization level, industrial structure, and government investment can promote the EWP, while the industrialization degree and the opening level had a negative impact on it [21]. In addition, other researchers mentioned that economic growth, industrialization, and government macro-control had significantly negative restraining effects [22]. Feng claimed that the main force to improve EWP has changed from industrial structure green adjustment to green total factor productivity [23]. Wang divided factors influencing EWP into four categories, which are economy, technology, subjective welfare, and objective welfare [19]. Moreover, for the spatial visualization and evolution characteristics, researchers are more likely to calculate the EWP and related objectives of different regions and compare them to each other in an earlier year. For example, Bian and Hou evaluated the EWP of 30 cities in China and the results show the average urban EWP, ranking of each city based on its EWP, as well as the ranking of different regions [20,24,25]. In addition, there is a similar work by Song that analyzes the EF, HDI, and EWP of four major island regions in China [26]. This approach is also used by Zhang to assess the EWP around the world, which indicates that developed countries (except Romania) and the G20 countries (except India and Indonesia) are generally less ecologically efficient in improving human well-being [27]. Zimmermann construct a evaluation system based on environmental health, ecosystem vitality, DMC, Gini, unemployment rate, and long-term unemployment and suggested that a partial overlap exists between conventional
“world of welfare states” and “worlds of eco-welfare states” [28]. However, nowadays, more studies focus on the combined impact of the factors mentioned above and the spatial characteristic on EWP. They also aim to determine the characteristics deeply through prediction models. Bian proved that the negative spatial spillover effect of the urbanization level on the EWP was significant [29]. Song used the gray prediction model [26], and Yao used Markov probability transfer matrices [30] to predict the evolution trend for a certain future period of EWP.

It is said that environmentally responsible behavior and sustainability policy adoption have a strong link. Now, sustainable and innovated development is the key policy target [31]. Moreover, carrying out government guidelines, assimilating sustainability in action-oriented plans, furthering sustainable outcomes, and advancing infrastructure backing and sustainable facilities are effective determinants influencing environmentally responsible behavior [32], which is critical to the development of EWP.

We can find that EWP is suitable indicator for green credit. Moreover, there may be some form of relationship between them. Some studies support that there is an inverted “U”-shaped relationship between EWP and economic growth [7,33], which indicates that economic growth depends on nature consumption. Moreover, Dietz [6] showed a U-shaped relationship between GDP per capita and the environmental intensity of human well-being (EIWB), where EIWB is the inverse of EWP. Thus, there is no doubt that EWP has an inverted “U”-shaped relationship with economic growth. Guo found that green credit can improve the green economy. However, the green economy represents economic growth with less pollution [34]. In addition, Wang claimed that green credit could improve financial performance in China [35]. In summary, we propose the following hypothesis: there is an inverted U-shaped relationship between EWP and green credit.

3. Datasets

3.1. Variables

3.1.1. Dependent Variable

The dependent variable of this study is \( EWP \). \( EWP \) is the ratio of social welfare and \( EF \).

\[
EWP = \frac{\text{social welfare}}{EF} \tag{1}
\]

Based on Equation (1), Zhu Dajian [7] combined the research on \( EF \) and HDI since the 1990s and expressed \( EWP \) as:

\[
EWP = \frac{HDI}{EF} \tag{2}
\]

3.1.2. Core Independent Variable

The core independent variable is the amount of green credit. There are four main categories of green credit measurement in academia in China now, namely the balance of green credit, the balance of energy-saving and environmentally friendly loan projects, the balance of interest expenses of the six high-energy-consuming industries, and the bank loans in industrial pollution control investments. Since the green credit policy was formally launched in 2007, it has been difficult to obtain the balance of green credit in China in 2007. Thus, we select the loan balance of energy-saving and environmentally friendly projects from 2004 to 2017 as the standard for measuring green credit.

3.1.3. Other Independent Variables

When considering the mechanism of green credit, we will include the interaction between green credit and \( EF \) in the empirical model. As for social welfare, it has been pointed out that the indicators of social welfare are divided into two major categories: subjective welfare and objective welfare [36]. Because subjective welfare is difficult to describe quantitatively, only objective welfare is considered in this study, which is mainly measured by three indicators: GDP, education per capita, and LEB. Moreover, we will
include the interaction between green credit and the above variables. In this study, domestic GDP is chosen as the measure of GDP, and the evaluation system of educational attainment per capita is constructed by the entropy method with the annual enrollment of each degree.

3.2. Data Resources

Data on the balance of energy-saving and environmentally friendly loans come from the China Banking Industry Social Responsibility Report, published annually by the China Banking Association. Data on China’s HDI come from the Human Development Reports website, operated by the United Nations Development Programme (UNDP). China’s EF data come from the Global EF Network. Since the latest version is only updated to 2017, we will no longer collect data above from 2018 and beyond.

The data on LEB and domestic GDP can be obtained from the World Bank database and the National Bureau of Statistics in China, respectively. Since China has a nine-year compulsory education system, the number of enrollments in secondary school and below has little impact on the per capita education level. Only the annual enrollment of specialist, undergraduate, master’s, and doctoral courses is considered as a ranking reference factor in this study. The data can be obtained from the National Bureau of Statistics in China too.

4. Methods

The flowchart in Figure 2 depicts the ideal solutions for this paper.

![Figure 2. The flowchart.](image)

4.1. Data Pre-Processing

4.1.1. Entropy System

A matrix is constructed, where \( x_{n1}, x_{n2}, x_{n3}, x_{n4} \) represent enrollments in year \( n \) of specialist, undergraduate, master’s, and doctoral courses:

\[
X = \begin{bmatrix}
  x_{11} & x_{12} & x_{13} & x_{14} \\
  \vdots & \vdots & \vdots & \vdots \\
  x_{n1} & x_{n2} & x_{n3} & x_{n4}
\end{bmatrix}
\]  

(3)

\[
p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}
\]  

(4)
\[ e_j = -k \sum_{i=1}^{n} p_{ij} \left( k = \frac{1}{\ln n} \right) \]  

\[ w_j = \frac{1 - e_j}{\sum_{k=1}^{n} 1 - e_k} \]  

Then, we covert it into a normalized matrix by Equation (4) and calculate the entropy value and weight coefficient of each indicator by Equations (5) and (6). Finally, each column is multiplied by the corresponding \( w_j \) \((j = 1, 2, 3, 4)\) and summed to obtain the score for each year:

\[ h_j = \sum_{i=1}^{n} x_{ij} \times w_j \]  

Table 1 presents the education level, where \( w \) is the weight coefficient of each indicator. In this study, ratings are used as a measure of education level each year. We can see that the education level rises each year.

| Year | Specialist | Undergraduate | Master | Doctor | Score |
|------|------------|---------------|--------|--------|-------|
| 2004 | 237.4      | 209.9151      | 27.3002| 5.3284 | 146.7103 |
| 2005 | 268.1      | 236.3647      | 31.0037| 5.4794 | 165.4489 |
| 2006 | 293        | 253.0854      | 34.197 | 5.5955 | 179.2289 |
| 2007 | 283.8      | 282.0971      | 36.059 | 5.8022 | 185.8729 |
| 2008 | 310.6      | 297.0601      | 38.668 | 5.9764 | 199.5525 |
| 2009 | 313.4      | 326.1081      | 44.9042| 6.1911 | 211.0866 |
| 2010 | 310.5      | 351.2563      | 47.4415| 6.3762 | 218.6669 |
| 2011 | 324.9      | 356.6411      | 49.4609| 6.5595 | 225.3658 |
| 2012 | 314.8      | 374.0574      | 52.1303| 6.837  | 228.3545 |
| 2013 | 318.4      | 381.4331      | 54.0919| 7.0462 | 232.2989 |
| 2014 | 338        | 383.4152      | 54.868 | 7.2634 | 239.2402 |
| 2015 | 348.4      | 389.4184      | 57.0639| 7.4416 | 244.9321 |
| 2016 | 343.2      | 405.4007      | 58.9812| 7.7252 | 248.8043 |
| 2017 | 350.7      | 410.7534      | 72.2225| 8.3878 | 256.3377 |
| \( w \) | 0.3111257 | 0.3100538 | 0.2614999 | 0.1173206 | |

### 4.1.2. Dimensionless Data

Since the \( HDI \) is a dimensionless value between 0 and 1, we should also standardize the \( EF \):

\[ EF^* = \frac{\ln EF - \ln EF_{\text{min}}}{\ln EF_{\text{max}} - \ln EF_{\text{min}}} \]  

\[ EWP = \frac{HDI}{EF^*} \]  

A wide disparity leads to computational error. We continue the dimensionless treatment for the above variables. The overall maximum and minimum values are unknown. Thus, we will adopt the z-score method.

\[ x = \frac{x - \text{mean}}{\text{sd}} \]  

### 4.2. The Relationship between Green Credit and EWP

We assume an inverted U-shaped relationship between EWP and green credit. Thus, EWP is a quadratic function of green credit. Moreover, economic behavior for improving the environment cannot yield results immediately. To eliminate the effects of latency, we included the lag period for EWP in the study. The lag period can be decided by the Box–Jenkins method.
Based on the result, drawing on some similar research frameworks, the following data model is developed in this study [37]:

\[
EWP_t = \alpha + \beta_1 EWP_{t-1} + \beta_2 EWP_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \epsilon
\]  
(11)

where \(EWP_t\) refers to EWP at time \(t\); \(EWP_{t-1}\) and \(EWP_{t-2}\) refer to EWP lagged one period and two periods, respectively. \(Loan_t\) is the core explanatory variable, green credit. With 2003 as the base period, the difference between each year and 2003 is set as the time term \(t\). The time term \(t\) and its squared \(t^2\) can control for time trends and nonlinear changes in the dependent variable. \(\epsilon\) is the random error.

4.3. Robustness Test

Some researchers defined EWP as the ratio of LEB and EF [36].

\[
EWP^* = \frac{LEB}{EF}
\]  
(12)

\(EWP\) will be replaced by \(EWP^*\) in Equation (11).

\[
EWP^*_t = \alpha + \beta_1 EWP^*_{t-1} + \beta_2 EWP^*_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \epsilon
\]  
(13)

4.4. Factors Affecting Mechanism of Green Credit

When considering the interactions, the approach used in this study is to add the interaction between green credit and the corresponding item:

\[
EWP_t = \alpha + \beta_1 EWP_{t-1} + \beta_2 EWP_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \eta_1 \times Loan \times EF + \epsilon
\]  
(14)

Equation (14) explores the role of green credit in EWP by affecting the EF. If the impact of green credit on EWP becomes stronger as EF increases, \(\eta_1\) is significantly positive.

\[
EWP_t = \alpha + \beta_1 EWP_{t-1} + \beta_2 EWP_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \eta_2 \times Loan \times GDP + \epsilon
\]  
(15)

Equation (15) explores the role of green credit in EWP by affecting GDP. If the impact of green credit on EWP becomes stronger as GDP increases, then \(\eta_2\) is significantly positive.

\[
EWP_t = \alpha + \beta_1 EWP_{t-1} + \beta_2 EWP_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \eta_3 \times Loan \times LEB + \epsilon
\]  
(16)

Equation (16) explores the role of green credit in EWP by affecting LEB. If the impact of green credit on EWP becomes stronger as LEB increases, \(\eta_3\) is significantly positive.

\[
EWP_t = \alpha + \beta_1 EWP_{t-1} + \beta_2 EWP_{t-2} + \beta_3 Loan_t + \\
\beta_4 Loan_t^2 + \gamma_1 t + \gamma_2 t^2 + \eta_4 \times Loan \times EDU + \epsilon
\]  
(17)

Equation (17) explores the effect of green credit on EWP by influencing the per capita educational attainment, where \(EDU\) represents the per capita educational attainment. If the impact of green credit on EWP becomes stronger as EDU increases, \(\eta_4\) is significantly positive.
4.5. Prediction for EWP by ARIMA

We try to predict the EWP when we continue issuing more green credit. Assuming that the current scale of green credit issuance in China is increasing yearly and is proportional to time, we will use time instead of green credit in the subsequent predictions, which can also illustrate the direction of EWP when more green credit is issued.

ARIMA is short for Autoregressive Integrated Moving Average model. In the ARIMA(p,d,q) model, AR represents “autoregressive”, and p is the number of autoregressive times. MA represents the “sliding average”, q is the number of sliding average terms, and d is the number of difference orders required to obtain a smooth series.

The mathematical description of the ARIMA model is:

\[
\Delta^d EWP_t = \theta_0 + \sum_{i=1}^{p} \phi_i \Delta^d EWP_{t-1} + \epsilon_t + \sum_{j=1}^{q} \theta_j \phi_{t-j}
\]

where \(\Delta^d EWP_t\) denotes the series of \(EWP_t\) after \(d\) difference transformations, and \(EWP_t\) denotes the EWP at time \(t\). \(\epsilon_t\) denotes the random errors at time \(t\), which are mutually independent white noise series and obey a normal distribution with mean 0 and variance constant \(\sigma^2\). \(\phi_i (i = 1, 2, 3, \ldots, p)\) and \(\theta_j (j = 1, 2, 3, \ldots, q)\) are the parameters to be estimated, whose orders are \(p\) and \(q\). In conclusion, the above model is denoted as ARIMA(p,d,q).

5. Computational Method

Equations (11), (13)–(17) were solved by R 4.1.1 by the difference GMM method. First, the OLS method was used, and there was an unfitting result.

Table 2 shows the result of the VIF test, which is used to determine whether there is the multicollinearity between independent variables. We can see that the values of VIF are all less than 5, indicating that there is no multicollinearity. Thus, a serious endogeneity exists in the models and we choose the difference GMM method. The GMM method does not require knowledge of the exact distribution of the random error terms, allowing for heteroskedasticity and serial correlation of the random error terms. It yields a more efficient parameter estimation than other parameter estimation methods.

Table 2. The result of VIF test.

| Variable     | VIF     |
|--------------|---------|
| \(EWP_{t-1}\) | 4.034447 |
| \(EWP_{t-2}\) | 4.034447 |
| \(Loan_t\)   | 2.320107 |
| \(Loan^2_t\) | 2.320107 |

6. Results

6.1. The Relationship between Green Credit and EWP

The results in Table 3 show a significant inverted U-shaped relationship between green credit and EWP. By simplifying the model and performing a simple calculation (Simplify the model to a primary binary function and use \(x = -b/2a\) to calculate the value of \(x\) corresponding to the peak.), it is roughly concluded that the EWP peaks when the balance of energy-saving and environmental protection loans approaches 2934.2 billion yuan, which corresponds to the loan balance between 2015 and 2016. To give non-Chinese readership a better visualization of the value, we use the average dollar exchange rate 6.6423 in 2017 and calculate the sum in USD, which is 441.7446 billion dollars.

In addition, the coefficient of the impact of EWP of lag one on current EWP is significantly positive, indicating that it has a positive contribution. In contrast, the effect of EWP of lag two on current EWP is quite negative, which means that EWP of lag two has a suppressive effect on current EWP. It shows that EWP is currently fluctuating, and the
boosting effects brought by EWP in the previous period will become a suppressing effect in the next period.

Table 3. The result of relationship between green credit and EWP.

| Variable     | Coefficient       |
|--------------|------------------|
| EWP$_{t-1}$ | 0.391 ***        |
|              | (20,779,897)     |
| EWP$_{t-2}$ | −0.363 ***       |
|              | (−22,509,497)    |
| Loan$_t$    | 0.082 ***        |
|              | (25,346,805)     |
| Loan$_{t}^2$| −0.079 ***       |
|              | (−59,106,851)    |

Z-statistics in square brackets below the regression coefficients. ***, indicate that the coefficient estimates are significantly different from 0 at the 0.1%, 1%, 5% level, respectively.

6.2. Robustness Tests

Table 4 shows the result of robustness tests. According to the result, it is clear that the effects of the second lag of EWP become insignificant when the measure of EWP is changed from the human development index to the life expectancy of development at birth. The reasons are as follows. The HDI is measured by three dimensions, income, longevity, and education, and the mechanism of action suggests that EWP fluctuates because of the opposing effects of income and longevity, and after replacing the measure, EWP no longer fluctuates due to the lack of the impact of income, but has a positive lagged-period effect. However, the coefficients before green credit and its quadratic term indicate that the relationship between green credit and EWP is still inverted U-shaped. Hence, the model passes the robustness test.

Table 4. The robustness result of relationship between green credit and EWP.

| Variable     | Coefficient       |
|--------------|------------------|
| EWP$_{t-1}$ | 0.513 ***        |
|              | (65,781,699)     |
| EWP$_{t-2}$ | −0.353           |
|              | (NaN)            |
| Loan$_t$    | 0.220 ***        |
|              | (12,402,280)     |
| Loan$_{t}^2$| −0.197 ***       |
|              | (−21,252,869)    |
| AR(2) P     | 0.371            |
| Hansen test P| 1                |

Z-statistics in square brackets below the regression coefficients. ***, indicate that the coefficient estimates are significantly different from 0 at the 0.1%, 1%, 5% level, respectively. NaN (Not a Number) represents null data.

6.3. Factors Affecting the Mechanism of Green Credit

According to Table 5, in terms of significance, we first exclude the analysis of the role of educational attainment.

Next, we analyze ecological footprint, national income, and life expectancy. By analyzing the interaction term between green credit and them, we can see that the impact of green credit on EWP becomes weaker by 0.241 and 23.494 as EF and GDP increases by 1, and the effect of green credit on EWP becomes stronger by 7.095 as LEB growth by 1. It indicates that when people use more natural resources, the effect of green credit will become minimal, which is supported by the fact that green credit is proposed to reduce the
use of natural resources. In economically developed areas, the role of green credit is also not very obvious.

**Table 5.** The results of how EF, GDP, LEB, EDU influence the mechanism between green credit and EWP.

|                     | Equation (14) | Equation (15) | Equation (16) | Equation (17) |
|---------------------|---------------|---------------|---------------|---------------|
| $EWP_{t-1}$         | 0.339***      | −0.511***     | −0.002***     | −0.193        |
|                     | (14,031,917)  | (36,900,052)  | (35,425)      | (NaN)         |
| $EWP_{t-2}$         | −0.494        | −0.309***     | −0.537        | −0.799        |
|                     | (NaN)         | (55,637,636)  | (NaN)         | (NaN)         |
| $Loan_1$            | 1.81***       | 15,851***     | −3.647***     | 6.512         |
|                     | (4,306,730)   | (29,593,906)  | (−61,449,023)| (NaN)         |
| $Loan_2$            | −0.038        | 24,975***     | −1.326***     | 0.685         |
|                     | (NaN)         | (27,070,417)  | (−155,852,296)| (NaN)         |
| $Loan:EF$           | −0.241***     | 7,095***      | −111,571,680  | −8.687        |
|                     | (−4,330,403)  |               |               | (NaN)         |

AR(2) P 0.371 0.371 0.371 0.371
Hansen test P 1 1 1 1

Z-statistics in square brackets below the regression coefficients. ***, indicate that the coefficient estimates are significantly different from 0 at the 0.1%, 1%, 5% level, respectively. NaN (Not a Number) represents null data.

6.4. Prediction for EWP by ARIMA

Before deciding on the orders p and q, we need a stable sequence. The ADF test (Augmented Dickey–Fuller Testing) is one of the most commonly used unit root tests. If the test result rejects the original hypothesis, i.e., $p < 0.05$, the series is smooth.

From Table 6, it can be seen that a smooth series could be obtained after third-order differencing.

**Table 6.** The result of ADF test.

| Confidence Level | t-Statistic | p     |
|------------------|-------------|-------|
| First-order difference | −2.4081 | 0.1395 |
| 1%                | −4.3362     |       |
| 5%                | −3.3672     |       |
| 10%               | −2.803      |       |
| Second-order difference | −1.8793 | 0.3419 |
| 1%                | −4.6652     |       |
| 5%                | −3.3672     |       |
| 10%               | −2.803      |       |
| Third-order difference | −3.5789 | 0.0061 |
| 1%                | −4.6652     |       |
| 5%                | −3.3672     |       |
| 10%               | −2.803      |       |

After determining the difference order, we assess order p and q by plotting the characteristics of the ACF (Auto-Correlation Function) and the PACF (Partial Auto-Correlation Function), as well as the AIC and BIC quasi-measures.

From Figure 3 and the results of AIC and BIC quasi-measures, we can identify the use of ARIMA(2,3,2) as a time series model of EWP.
Before applying ARIMA(2,3,2) for prediction, Figure 4 compares the actual curve of EWP and the curve forecasted by the model. We can see a small gap between the actual value and projected value (Table 7), which proves the great accuracy. In addition, the accuracy of the trend is more important than the value. The slopes of the actual curve before 2013 are always negative. Moreover, the changing pattern is a high slope in one period and low pitch in the next. The design is in line with the results in Table 3, which indicates that the coefficients of EWP lagged by one and two periods are positive and negative. The slopes of the forecasted curve are similar to the slopes of the actual curve, except the slope from 2011 to 2012, which is positive. However, the overall trends are identical. The points of 2013 are almost overlapping. After 2013, both slopes are positive. In addition, both curves reach a peak in 2016, corresponding to the previous conclusion.

Table 7. The gap of EWP between prediction and reality.

| Year | Real Value | Forecasted Value | Gap   |
|------|------------|------------------|-------|
| 2007 | 1.02361906 | 1.004907         | 0.018712 |
| 2008 | 1.02418241 | 0.985563         | 0.038619 |
| 2009 | 0.97098372 | 0.966173         | 0.004811 |
| 2010 | 0.95070116 | 0.82951          | 0.121191 |
| 2011 | 0.93695573 | 0.819635         | 0.117321 |
| 2012 | 0.95452049 | 0.822729         | 0.131791 |
| 2013 | 0.96382111 | 0.812425         | 0.151396 |
| 2014 | 1.00523427 | 0.822759         | 0.182475 |
| 2015 | 1.0398292  | 0.838639         | 0.20119 |
| 2016 | 1.08545006 | 0.867779         | 0.217671 |
| 2017 | 1.069197   | 0.859603         | 0.209594 |

Given the ARIMA(2,3,2), there is an inverted U-shaped relationship between EWP and green credit from the continuously falling curve from 2018 to 2023 (Table 8). However, EWP no longer declines when green credit grows to a particular scale, but fluctuates to a constant within a specific interval. Moreover, the changes in curve slope present the instability of EWP (Figure 5).
Figure 4. The gap of EWP between prediction and reality.

Table 8. The results of prediction of EWP.

| Time (Years) | EWP  |
|--------------|------|
| 2018         | 0.807|
| 2019         | 0.775|
| 2020         | 0.764|
| 2021         | 0.741|
| 2022         | 0.739|
| 2023         | 0.725|
| 2024         | 0.732|
| 2025         | 0.727|
| 2026         | 0.743|
| 2027         | 0.747|

Figure 5. Time–EWP curve.

7. Conclusions

In recent years, active discussion has focused on the issuance of green credit. Our study is the first to analyze EWP under the green credit policy, providing a fresh perspective for the assessment of green credit. We include two empirical models for determining the relationship between EWP and green credit, as well as factors affecting the mechanism of
green credit. In addition, we construct a time series model, ARIMA(2,3,2), to predict the trend of EWP when more green credit is issued.

The first empirical model shows that the relationship between EWP and green credit is an inverted “U” shape, and the second indicates that the effect of green credit on EWP becomes weaker by 0.241 and 23.494 as EF and GDP increases by 1, and the impact of green credit on EWP becomes stronger by 7.095 as LEB increases by 1. GDP and EF have a suppressive effect on the impact of green credit on EWP, and lifespan can positively affect the mechanism. In addition, the ARIMA(2,3,2) model shows that EWP fluctuates to a plateau within a specific interval after a certain amount of green credit is issued. All the results are in line with developments in Table 1: EWP peaked between the years 2015 and 2016 when loans approached 2934.2 billion yuan, which equals 441.7446 billion dollars, and this can prove the accuracy of the model.

In summary, the main conclusions that can be drawn from this work are as follows.

1. Banks may control the issuance volume of green credit. Combining the above results, we argue that it is not appropriate to issue green credit excessively under the current mechanism, and the actual issuance volume of green credit should be determined by market players as well as multifaceted policies. Blind issuance of green credit will only show that the expected goal cannot be achieved by mass production. Meanwhile, the government can also gradually shift its focus to other green financial products, such as green insurance and green bonds.

2. The government should focus on the main contradictions in the development of green credit. The root cause of the problems caused by green credit is not the policy itself but the diminishing ecological resources. There is a lower limit on the consumption of fixed ecological resources for production work. Green credit depresses the upper limit of production consumption, but it does not solve the problem of the lower limit of production. The external environment of China’s economic development is undergoing profound changes. Grasping the main contradictions in the development process is the focus of the current financial work, which also directly affects the ultimate effectiveness of the financial work.

3. Enterprises can promote the transformation by green credit. Their changes need to avoid a “one-size-fits-all” approach. The state should issue green credit to encourage heavily polluting enterprises to gradually transform into new energy ones, instead of preventing their production by increasing financing restrictions. In addition, the state can also control pollution emissions efficiently by adjusting the carbon tax for heavy polluters to achieve benign control [38]. The fluctuation of EWP shows that the implementation of relevant policies in China is not fully in place, and there is a phenomenon of “one year lose, one year tight” in the process of implementation. The relevant departments need to persistently adhere to the green development strategy and implement environmental protection policies. Moreover, the news about such strategies should be tightly controlled in order not to mislead the masses [39].

In this study, there are still many weaknesses. For example, to obtain the macro insight, we ignore some details, such as data from different provinces in China. Moreover, because the HDI and EF are measured by international organizations, we do not have access to these two pieces of data at the provincial level and below. In addition, the methods used in this paper are all traditional, at the provincial level and below.

Thus, in the future, we will perform more detailed research, which can build a new system for evaluating the EWP of different provinces in China, instead of using the indicators HDI and EF.

However, we attempt to solve it from a modeling perspective. The choice of the method becomes more critical when dealing with small samples. We use the entropy method, auto-correlation function, and other methods to extract the features inside the data. Moreover, the difference GMM method is used for regression, which eliminates the endogeneity existing in both empirical models. In addition, we continue to follow the
Many countries already have a well-established standard green credit system—the Equator Principles. However, the emerging markets, led by China, are still going through the same changes that the developed countries went through decades ago [40]. Thus, based on the analysis in China, we hope to provide some guidelines for all emerging markets.

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