

Original Research

Can CO₂ Emission and Economic Loss Drive Forestry Productivity in the Context of Low Carbon Economy in China

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Abstract

In the context of global warming, low-carbon economy has attracted more and more countries' attention. Using second-generation unit root CIPS test and mean group (MG) estimation, we examined the impact of CO₂ emissions and economic loss on forest productivity with panel data on 30 Chinese provinces from 2004 to 2020. The results showed that CO₂ emissions and economic loss had significant negative impacts on it, technical innovation had positive impacts on it, and the share of secondary industry had negative impacts on it. Regarding regional heterogeneity, CO₂ emissions in west China had the greatest impact on forest productivity, followed by east China. The coefficients of economic loss in west, east and middle China were all negative, but those in east and middle China did not pass significance test. The coefficients of technical innovation in east and west China were positive, with the coefficient in east China not passing significance test. In order to improve forest productivity and achieve carbon neutrality, it is necessary to reduce CO₂ emissions, curb economic losses caused by factors like environmental pollution, natural disasters, geological disasters and forest fires, improve technological innovation, promote industrial upgrade, and implement differentiated policies based on local conditions.

Keywords: carbon emissions, economic loss, forest productivity, mean group estimation, dynamic OLS

Introduction

In the context of global warming, low-carbon economy has attracted more and more countries' attention. China is no exception. In order to cope with climate change, China is developing a Low-carbon economy. Forestry is an important part of China's national economy and a key element of building

a well-off society in an all-round way. At a voluntary tree planting activity held on March 20, 2022 in Beijing, General Secretary Xi Jinping said that the forest is a reservoir, a money bank, a grain depot, and a "carbon bank". Forest relates to the realization of the goals of carbon peak and carbon neutrality. In recent years, China's forestry sector develops rapidly. More investments in it are made and its output value continue to increase. Due to the scarcity of forest resources, reducing investment and improving forest productivity are the main means to promote forestry

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growth. Forest productivity is the basis for formulating policies on sustainable forest development. Therefore, calculating it and analyzing the impact of CO₂ emissions and economic loss on it are of great significance for the sustainable development of China's forestry, economy and society with high quality.

Existing studies on forest productivity focuses on its measurement, influencing factors and impacts on CO₂ emissions, in which it was mainly measured through data envelopment analysis (DEA) [1-3], stochastic frontier analysis (SFA) [4-5], DEA-Malmquist productivity index (MPI) and C-D function-based productivity index [6-9], and sometimes calculated with slack based measure (SBM) [10-12].

There have been discussions on factors influencing forest productivity [13-16]. For example, Lin et al. (2020) checked the impacts of foreign direct investment on the productivity of Chinese forestry companies and found that the impacts were complicated [17]. Wu and Zhang (2020) examined the impacts of internet on forestry and how do different internet technologies optimize and coordinate clean production [18]. The digital economy can significantly promote an improvement in forestry green total factor productivity [19]. They found that technology-based internet and platform-based internet produce positive impacts on forestry clean production in the short term, of which technology-based internet exerts a greater impact. But in the long run, technology-based internet hinders the improvement of green technology efficiency and the progress of green technologies. Xiong et al. (2018) measured the regional differences of forest productivity in northeast China and identified six factors influencing it [20]. The conclusion was that the per capita GDP, forest coverage rate, educational background of practitioners and quantity of township forestry technology stations are positively related to forest productivity, whereas collective forestry tenure reform produces negative impacts on it.

Many scholars worked on the impact of forest area and forest management on CO₂ emissions [21]. Koonthar et al. (2021) probed into the relationships among CO₂ emissions, renewable energy consumption, forestry and agricultural added value between 1998 and 2018. According to them, the decrease of CO₂ emissions was related to the increase of forest area both in the long run and short term [22]. Raihan and Tuspekova (2022) investigated the potential of forest reducing CO₂ emissions to realize sustainability in Malaysian environment based on time sequence data from 1990 to 2019. The results indicated that increased use of renewable energy and forest area can reduce CO₂ emissions [23]. Aziz and Mighri (2022) explored the role of forest activities in CO₂ emissions in different Chinese provinces with forest area and forest investment as sub-proxy variables. They revealed that forest investment is significantly negatively related to CO₂ emissions, while proper and continuous increase of forest management activities helps reduce CO₂ emissions [24]. Raihan et al. (2022) focused on how technological innovation

and forest area helped Bangladesh achieve environmental sustainability and found that technological innovation and forest area are conducive to achieving environmental sustainability through reducing CO₂ emissions [25]. Li et al. (2021) studied the role of forest management in controlling CO₂ emissions in China. The results suggested that forest investment and management not only reduce local CO₂ emissions, but also lower emissions in neighboring provinces [26]. Rehman et al. (2021) studied the influence of forestry production and crop production on CO₂ emissions in Pakistan. Long-term dynamic analysis reveals that forestry production and rainfall have constructive impacts on CO₂ emissions, whereas crop production has negative impacts on CO₂ emissions. Analysis of short-term data indicates that forestry production and crop production have a positive impact on CO₂ emissions [27]. Rehman et al. (2021) discussed the asymmetric impact of crop production and forestry production on CO₂ emissions in China from 1970 to 2017. They concluded that positive impacts on crop production deteriorate atmospheric quality in the long run by intensifying CO₂ emissions, and that forestry fluctuations do not have any significant impact on CO₂ emissions in China [28]. Liu et al. (2022) analyzed annual banking statistics of the World Bank from 1990 to 2020 to explore the asymmetric relationship between the development of China's agricultural and forestry, energy consumption and CO₂ emissions using Granger causality test [29]. They found that energy consumption, economic development, and CO₂ emissions boost agricultural and forestry growth; in the next three years, China's agricultural and forestry growth will slow down due to the three factors. Besides, China's CO₂ emissions were affected by the pulse responses of energy consumption and agricultural and forestry growth, falling first and then rising. A small number of sources focuses on the influence of forest productivity on CO₂ emissions. For example, Zhong and Wang (2021) calculated total factor forestry productivity and its factorization index using global DEA-Malmquist productivity index. They indicated that the influence of total factor forestry productivity on CO₂ emissions is in a U-shaped curve [30].

In summary, rich works on forest productivity lay a solid foundation for this study. However, they have the following shortcomings. First of all, most of them focus on the impact of forestry production and forestry area on CO₂ emissions, whereas few explore the impact of CO₂ emissions on forestry production, even fewer examine the influence of CO₂ emissions on forest productivity. Secondly, there are rare studies of the influence of economic loss caused by environmental pollution, natural disasters, geological disasters and forest fires on forest productivity. Thirdly, most of existing literature employs first-generation unit root test and traditional econometric methods. This study may make the following contributions. First, data of 30 Chinese provinces from 2004 to 2020 are analyzed to examine the impact of CO₂ emissions on

forest productivity. Second, the mean group (MG) estimation are used to investigate the impacts of direct economic loss caused by environmental pollution, natural disasters, geological disasters and forest fires on forest productivity. Third, robust second-generation econometric tests are conducted, including cross-sectional dependence, second-generation panel unit (cross-sectionally augmented, IPS) CIPS test, slope heterogeneity and mean group test. Fully modified OLS (FMOLS) and dynamic OLS (DOLS) are used to check the stability of results. Fourth, this study offers theoretical and empirical reference for coordinated, sustainable and high-quality development of green forestry.

Materials and Methods

Data used herein mainly come from the China Statistical Yearbook, the China Forestry Statistical Yearbook, the China Statistics Yearbook on Environment, the China Rural Statistical Yearbook, the China Statistical Yearbook on Science and Technology, the China Land and Resources Almanac, statistical yearbooks of 30 Chinese provinces under study, the website of China National Bureau of Statistics, and the website of 30 provincial (municipal) bureaus of statistics.

Scope of Study

This paper mainly probes into the influence of CO₂ emissions and economic loss on forest productivity in 30 provinces in the Chinese Mainland from 2004 to 2020. Tibet is not included because of a lack of data for many years.

Methods

Entropy Weight Method

We drew on the carbon productivity measurement method used by the Organization for Economic Cooperation and Development (OECD) to calculate forest productivity (FP). The first step was to build an indicator system and obtain forest indicator (FI), for which entropy weight method was used. The entropy weight method can make full use of the original data, not only with higher accuracy and objectivity, but also with better interpretation of the obtained results. The FP formula is as follows:

$$FP = \frac{FI}{GDP} \tag{1}$$

China upholds new development concepts, drives high-quality development, and implements the strategy of innovation-driven development, which also applies to forestry. By advocating the philosophy that lucid waters

and lush mountains are invaluable assets, it promotes the high-quality development of forestry. We built a forest indicator evaluation system following the concept of “innovation, green, clean and security”. Drawing on related research, we set the evaluation system as below based on operability and data availability.

The weights of the indicators are calculated using entropy method. The steps of calculation are:

Firstly, the selection of indicators. We employed *s* years, *n* provinces, *m* indices, and P_{ij} the *j*th index value of province *i* in year *t*.

Secondly, the standardization of indicators. In order to eliminate differences in the unit and quantity dimension of indicators, basic indicators for the FI of 30 provinces were standardized with range method. Different standardization calculations were applied to measure positive indicators and negative indicators.

The formula for standardizing positive indicators is:

$$P'_{ij} = \frac{P_{ij} - \min(P_{ij})}{\max(P_{ij}) - \min(P_{ij})} \tag{2}$$

The formula for standardizing negative indicators is:

$$P'_{ij} = \frac{\max(P_{ij}) - P_{ij}}{\max(P_{ij}) - \min(P_{ij})} \tag{3}$$

We performed translation of coordinates on standardized data:

$$P''_{ij} = 1 + P'_{ij} \tag{4}$$

Thirdly, we calculated the entropy value h_j of indicator *j*,

$$h_j = -k \sum_{t=1}^s \sum_{i=1}^n M_{tij} \ln(M_{tij}) \tag{5}$$

among which $k = \frac{1}{\ln(sn)}$, $M_{tij} = \frac{P''_{ij}}{\sum_{t=1}^s \sum_{i=1}^n P''_{ij}}$

Fourthly, we calculated the weight W_j of indicators based on entropy h_j .

$$w_j = \frac{1 - h_j}{\sum_{j=1}^m (1 - h_j)} \quad 0 \leq w_j \leq 1, \quad \sum_{j=1}^m w_j = 1 \tag{6}$$

Finally, based on the above calculations, the FI_{*it*} can be obtained:

$$FI_{it} = \sum_{j=1}^m w_j P'_{ij} \tag{7}$$

With the help of evaluation indicator system and above measurement methods, the FI of the 30 provinces in China from 2004 to 2020 were obtained.

Mean Group Estimator

We performed cross-sectional dependence tests before measurement and analysis (Pesaran, 2015) [31]. Cross-sectional dependence is related to several factors like economic proximity, residual interdependency, and hidden observed and unobserved factors [31-32]. If it is ignored, there may be biases and inaccurate statistics in panel data estimation [31].

Slope heterogeneity is another problem to be considered [33]. The method used by Pesaran and Yamagata (2008) is adopted in this study [34], which performs better if the sample size is small [35]. The null hypothesis for slope heterogeneity is that slope parameters are homogeneous, while the alternative hypothesis is that slope parameters are heterogeneous.

Next, we tested the stationarity of panel data. Since first-generation unit root tests such as ADF and IPS do not take into consideration slope heterogeneity and cross-sectional dependence, we performed CIPS test [36].

Afterwards, panel co-integration tests developed by Pedroni (2004), Kao's (1999) and Westerlund (2005) were conducted to check long-term co-integration among variables. This makes test results more reliable and consistent [37-39].

Mean group estimator was used to evaluate the impact of CO₂ emissions and economic loss on forest productivity in China [40]. Long-term coefficients were obtained using auto-regressive distributed lag (ARDL) model [41], as Kusairi et al. (2019) [42].

$$Y_{it} = \alpha_i + \gamma_i Y_{it-1} + \beta_i X_{it} + u_{it} \tag{8}$$

Y_{it} is the dependent variable, X_{it} the independent variable, and β_i the estimator coefficient of a particular province.

The long-run parameter of province i is (Kusairi et al., 2019):

$$\theta_i = \frac{\beta_i}{1 - \gamma_i} \tag{9}$$

Mean group estimators for the full panel were obtained with the equation below (Kusairi et al., 2019):

$$\hat{\theta} = \frac{1}{N} \sum_{i=1}^N \theta_i, \quad \hat{\alpha} = \frac{1}{N} \sum_{i=1}^N \alpha_i \tag{10}$$

Mean group allows changes in the variance of intercepts, short-term parameters and cross-group errors. It ensures stable consistency of long-term coefficients [43].

FMOLS and DOLS

FMOLS and DOLS were adopted to check the robustness of results.

We applied Pedroni's (2000) fully modified OLS (FMOLS) to benchmark model to estimate the heterogeneous cointegration vectors of panel data [44]. Pedroni (2000) used the cointegration system below to analyze panel data [45]:

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{11}$$

When Y and X are cointegrated, Pedroni (2001) built a new equation to control the feedback effect of endogenous explanatory variables [46]:

$$Y_{it} = \alpha_i + \beta X_{it} + \sum_{k=-k_1}^{k_2} \gamma_{ik} \Delta X_{it-k} + \varepsilon_{it} \tag{12}$$

where $\zeta_{it} = (\varepsilon_{it}, \Delta X_{it})$, $\Omega_{it} = \lim_{T \rightarrow \infty} E \left[\frac{1}{T} \left(\sum_{t=1}^T \zeta_{it} \right) \left(\sum_{t=1}^T \zeta_{it} \right)' \right]$ is the long-term covariance of the above equation.

The matrix of long-term covariance was broken down into: $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$, in which Ω_i^0 indicates the covariance of the same period, and Γ_i the weighted sum of the autocovariance. The panel FMOLS formula is:

$$\beta_{FMOLS}^* = \frac{1}{N} \sum_{i=1}^N \left[\left(\sum_{t=1}^T (X_{it} - \bar{X}_i)^2 \right)^{-1} \left(\sum_{t=1}^T (X_{it} - \bar{X}_i) Y_{it}^* - T \gamma_i \right) \right] \tag{13}$$

$$Y_{it}^* = Y_{it} - \bar{Y}_i - (\hat{\Omega}_{2,1,i} / \hat{\Omega}_{2,2,i}) \Delta X_{it} \text{ and}$$

$$\hat{\gamma}_i = \hat{\Gamma}_{2,1,i} + \hat{\Omega}_{2,1,i}^0 - (\hat{\Omega}_{2,1,i} / \hat{\Omega}_{2,2,i}) (\hat{\Gamma}_{2,2,i} + \hat{\Omega}_{2,2,i}^0).$$

The DOLS representation is shown in Eq. (14).

$$\beta_{DOLS}^* = \left[\frac{1}{N} \sum_{i=1}^N \left(\sum_{t=1}^T Z_{it} Z_{it}' \right)^{-1} \left(\sum_{t=1}^T Z_{it} Y_{it}^* \right) \right] \tag{14}$$

Where $Z_{it} = (X_{it} - \bar{X}_i, \Delta X_{it-k}, \dots, X_{it+k})$ is $2(K+1) \times 1$ vector of regressors.

Model Specification

The following model was built to explore the impact of CO₂ emissions and economic loss on forest productivity:

$$FP_{it} = f(CE_{it}, EL_{it}, TI_{it}, SE_{it}) \tag{15}$$

Table 1. Forest indicator system

Dimension	Indicator	Indicator description	Indicator direction
Innovation	R&D funding intensity	R&D/ region GDP	+
	Full-time equivalent ratio of R&D personnel	Full-time equivalent of R&D personnel/ population at the end of the year (%)	+
	Number of per capita patents	Number of patents authorized/ total population at the end of the year (piece/ 10,000 people)	+
Green	Forest coverage	Forest area ÷ total land area × 100% (%)	+
	Forest stock volume	Forest stock volume (10,000 m ³)	+
	Living wood growing stock	Living wood growing stock (10,000 m ³)	+
Clean	Sulfur dioxide emissions	Sulfur dioxide emissions in industrial exhaust gas (10,000 tons)	-
	Chemical oxygen demand	Chemical oxygen demand in wastewater (10,000 tons)	-
	Ammoniacal nitrogen emissions	Ammoniacal nitrogen in wastewater (10,000 tons)	-
	Industrial solid waste	Industrial waste generated (10,000 tons)	-
	Forestry investment completion	Completion of forestry investment of the year (10,000 CNY)	+
Security	Number of forestry practitioners	Forestry practitioners at the end of the year (person)	+
	Forestry total output value	Total output value of forestry (100 million CNY)	+
	Afforestation area	Total afforestation area (hectare)	+
	Forest area	Forest area (10,000 hectares)	+

In the above equation, *i* refers to province, *t* means the year (from 2004 to 2020). How forest productivity was calculated has been explained above. CE indicates per capita carbon emissions (unit: tons of standard coal). Economic loss (EL) is the sum of direct economic losses brought by environmental pollution, natural disasters, geological disasters and forest fires (unit: 100 million CNY). Technical innovation (TI) is represented with the proportion of R&D expenditure in GDP (unit: %). SE refers to the industrial structure, which is expressed by the output value of the second industry (unit: %).

The form of regression of Eq. (15) is shown below:

$$FP_{it} = \delta_{1it} + \delta_{2it} CE_{it} + \delta_{3it} EL_{it} + \delta_{4it} TI_{it} + \delta_{5it} SE_{it} + \varepsilon_{it} \tag{16}$$

All variables are in natural logarithm. ε refers to error term.

Evaluation CE

As China didn't announce statistics of the CE of provinces from 2004 to 2020, we propose the formula below to calculate CE [47].

$$\sum_{i=1}^n CE_i = \sum_{i=1}^n E_i \times CF_i \times CC_i \times COF_i \times \left(\frac{44}{12}\right) \tag{17}$$

where *n* means type of energy, *E_i* the consumption of energy *i* calculated by standard coal, *CF_i*, *CC_i* and *COF_i* the heating value, carbon content and carbon oxidation

factor of energy *i*, and $CF_i \times CC_i \times COF_i \times \left(\frac{44}{12}\right)$ the CE

coefficient of energy *i*. Based on the heating value (CF), carbon content (CC) and carbon oxidation factor (COF) of various energy sources in the IPCC Guidelines for National Greenhouse Gas Inventory 2006 and the China Energy Statistical Yearbook 2019, the CE (unit: 10,000 tons of standard coal) of 30 Chinese provinces from 2004 to 2020 are calculated. Energy consumption and energy balance tables come from the Chinese Energy Statistical Yearbook from 2005 to 2021.

Descriptive statistics of variables are shown in Table 2. The mean values of forest productivity, CO₂ emissions, economic loss, technical innovation and the share of secondary industry are 0.2193, 10.5131, 106.6343, 1.5166 and 45.14.

Results

Cross-Sectional Dependence Test

Along with integrated development, Chinese provinces are increasingly interdependent, so the missing of cross-sectional dependence may lead to severe economic consequences [48-49]. Therefore, we discussed cross-sectional dependence with the help of the test method developed by Pesaran (2015) [31]. Table 3 presents the results, which indicate that all variables, including forest productivity, CO₂ emissions, economic

Table 2. Descriptive statistics.

	FP	CE	EL	TI	SE
Mean	0.2193	10.5131	106.6343	1.5166	45.1400
Median	0.1919	8.0227	78.2257	1.2214	46.6000
Max.	0.6663	54.3051	1221.6130	6.4400	61.5000
Min.	0.0285	1.4394	0.0143	0.1783	15.8000
S. D.	0.1326	8.0331	119.1549	1.0989	8.6217
Ske.	1.0250	2.2564	3.2040	2.0355	-1.0093
Kur.	3.7636	9.0239	21.1756	7.8859	3.9456
J.B.	101.6969	1203.903	7892.582	859.4967	105.5956
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	510	510	510	510	510

loss, technical innovation and the share of secondary industry, rejected the null hypothesis that cross-sectional dependence does not exist at the 1% significance level. In other words, it existed among all the variables studied.

Table 4 shows the result of slope heterogeneity test (Pesaran and Yamagata, 2008). $\hat{\Delta}$ and $\hat{\Delta}$ adjusted tests rejected the null hypothesis on slope homogeneity at the 1% significance level.

Panel Unit Root and Co-Integration Tests

Given the presence of cross-sectional dependence among variables and slope heterogeneity in our model, we used CIPS to better determine the property of unit root in the presence of cross-sectional dependence [50-51]. Table 5 shows the results. At the 10% significance level, all the variables rejected the null hypothesis concerning non-stationarity. In other words,

CIPS test showed all variables were stationary at the 1% significance level, i.e., I (0) stationarity.

We tried to find out whether there was long-term co-integration among variables using co-integration tests developed by Pedroni, Kao and Westerlund [38-39, 52]. Table 6 presents the results. Pedroni’s residual co-integration test showed that in both within and between dimension test, the null hypothesis was rejected, and variables in Eq. (16) were co-integrated. Kao test and Westerlund (2005) co-integration test showed there was co-integration among all the variables. The results are consistent, which indicates that all the variables were co-integrated. In other words, there was a stable and long-term relationship between variables in this study and forest productivity.

MG Regression Results

We explored the impact of CO₂ emissions, economic loss and other variables on forest productivity with mean group estimator (Pesaran, 1995). Table 7 shows the results. The coefficient of CO₂ emissions was significantly negative. CO₂ emissions and forest productivity were negatively correlated. The higher the CO₂ emissions, the lower the forest productivity.

Table 3. Results of Cross-section dependence test (CSD test).

Variables	CSD -Statistics Pesaran(2015) test[31]	P-Value	corr	abs (corr)
lnFP	42.43	0.000	0.493	0.550
lnCE	68.58	0.000	0.797	0.826
lnEL	11.39	0.000	0.132	0.236
lnTI	60.53	0.000	0.704	0.743
lnSE	61.58	0.000	0.716	0.716

Table 4. Pesaran and Yamagata (2008) SH test results.

	Value
$\hat{\Delta}$	10.845 ***(0.000)
$\hat{\Delta}$ Adjusted	13.482 ***(0.000)

Note: ***p <0.001. p-values are reported in parentheses.

Table 5. Results of CIPS unit root test.

Variables	At level			
	Intercept		Intercept & trend	
	Z[t-bar]	P-Value	Z[t-bar]	P-Value
lnFP	-2.051	0.020	-3.227	0.001
lnCE	-2.643	0.004	-0.512	0.304
lnEL	-11.434	0.000	-9.909	0.000
lnTI	0.579	0.719	-2.030	0.021
lnSE	-1.601	0.055	-1.504	0.066

Table 6. Results of panel cointegration tests.

Pedroni's residual cointegration test					
Within-dimension	Statistics	P-Value	Between-dimension	Statistics	P-Value
Panel v-stat	0.5626	0.2868			
Panel rho-stat	1.4502	0.9265	Group rho-Stat	4.2048	1.0000
Panel PP-stat	-6.6690	0.0000	Group PP-Stat	-6.7175	0.0000
Panel ADF-stat	-2.0901	0.0183	Group ADF-Stat	-1.5580	0.0596
Kao's (1999) Residual Cointegration Test			Westerlund (2005) Co-integration Test		
	t-Statistic	P-Value		Statistic	P-Value
ADF	-2.2062	0.0137	Variance ratio	-2.2915	0.0110
Residual variance	0.0057				
HAC variance	0.0044				

Note: The null hypothesis is that variables are not cointegrated, based on the hysteretic selection of SIC.

The coefficient of economic loss was also significantly negative. That is to say, the bigger the direct economic loss caused by environmental pollution and natural disasters in China, the lower the forest productivity. Conversely, the smaller the economic loss in China, the higher the forest productivity. The coefficient of technical innovation was significantly positive, which means China can increase forest productivity by expanding investments in R&D. The coefficient of the share of secondary industry was significantly negative, which means rising the share of secondary industry can reduce forest productivity.

Regional Analysis

China is a vast country. CO₂ emissions and economic loss vary in different regions, that is, they have regional heterogeneity. It is of great significance to study their impacts on forest productivity in different regions to gain a comprehensive understanding of forest productivity in China. We used mean group to estimate the impact of CO₂ emissions, economic loss and other variables on forest productivity in east, middle and west China. Results are shown in Table 8.

The coefficients of CO₂ emissions in east and west China were significantly negative. Increasing CO₂

emissions in both regions reduced forest productivity. Specifically, CO₂ emissions in west China had the greatest impact on forest productivity, followed by east China. The coefficients of economic loss in west, east and middle China were all negative, but those in east and middle China did not pass significance test. The coefficient of economic loss in west China was significantly negative, and economic loss in west China effectively reduced forest productivity. West China suffered the greatest economic loss caused by environmental pollution. As it had the most abundant forest resources, it embraced the highest forest productivity and the impact of economic loss on forest productivity there was the most significant. The coefficients of technical innovation in east and west China were positive, with that in east China not passing significance test. In other words, the rise of technical innovation in west China significantly increased forest productivity. The coefficients of industrial structure in east and middle China were significantly negative, which means increasing proportion of secondary industry can reduce forest productivity.

Robustness Test

In order to validate the above empirical results, we checked their robustness using FMOLS and DOLS. Estimation results of full panel data and each region are shown in Table 9. The results of FMOLS and DOLS full panel estimation were similar to those of mean group estimation. The coefficients of CO₂ emissions and economic loss were both significantly negative. That is, decreasing CO₂ emissions and economic loss effectively increased forest productivity. Both FMOLS and DOLS showed that the estimation coefficients of CO₂ emissions in west, east and middle China were significantly negative. In order to improve forest productivity in the three regions, it is necessary to lower CO₂ emissions.

Table 7. Full panel MG estimation results.

Variables	Coef.	Std. Err.	Z	P-Value
lnCE	-0.1765	0.0451	-3.91	0.000
lnEL	-0.0116	0.0067	1.72	0.085
lnTI	0.1206	0.0574	2.10	0.036
lnSE	-0.6562	0.1213	-5.41	0.000
Constant	1.2483	0.4727	2.64	0.008

Table 8. Regional MG estimation results.

	Eastern region			Central region			Western region		
Long-run estimation results									
Variables	Coef.	Std.Err.	P-value	Coef.	Std.Err.	P-value	Coef.	Std.Err.	P-value
lnCE	-0.1795	0.0810	0.027	-0.0752	0.0929	0.418	-0.2471	0.0625	0.000
lnEL	-0.0061	0.0082	0.464	-0.0034	0.0181	0.850	-0.0232	0.0102	0.023
lnTI	0.0811	0.0842	0.336	-0.0119	0.0990	0.904	0.2564	0.1035	0.013
lnSE	-0.9244	0.1804	0.000	-0.6363	0.1057	0.000	-0.4024	0.2542	0.114
Constant	1.6535	0.8566	0.054	1.2136	0.4575	0.008	0.8682	0.9465	0.359

Table 9. FMOLS and DOLS aggregate and regional estimations.

FMOLS									
	Full Panel		Eastern region		Central region		Western region		
Variables	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error	
lnCE	-0.1389***	0.032559	-0.1094*	0.0599	-0.1251*	0.0671	-0.1346***	0.0367	
lnEL	-0.0208***	0.007385	-0.0085	0.0059	-0.0049	0.0148	-0.0573***	0.0128	
lnTI	0.1299***	0.036602	0.0263	0.0453	0.1063*	0.0628	0.1055**	0.0509	
lnSE	-0.5107***	0.052460	-0.9175***	0.0864	-0.4929***	0.0710	-0.4051***	0.0852	
DOLS									
	Full Panel		Eastern region		Central region		Western region		
Variables	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error	
lnCE	-0.1345***	0.0347	-0.2309**	0.1047	-0.1052*	0.0613	-0.1385***	0.0468	
lnEL	-0.0208**	-0.0208	-0.0130	0.0127	-0.0310	0.0227	-0.0608***	0.0169	
lnTI	0.1024**	0.0403	0.0436	0.0771	0.1152*	0.0667	0.1200*	0.0620	
lnSE	-0.5489***	0.0504	-0.9216***	0.1359	-0.5480***	0.0591	-0.4336***	0.0980	

The coefficients of economic loss in west, east and middle China were all negative, but those in east and middle China did not pass significance test, while the coefficient of economic loss in west China did, which is consistent with MG estimation results. FMOLS and DOLS results showed that the coefficients of technical innovation in west and middle China were significantly positive, which means increasing R&D investment in the two regions can effectively increase forest productivity. FMOLS and DOLS estimation results in west, east and middle China were significantly negative, which means decreasing proportion of secondary industry in the three regions can effectively increase forest productivity. In conclusion, robustness test showed that mean group estimation in this study is robust.

Discussions

This paper studies the impact of CO₂ emissions and economic loss on forest productivity. In Table 7,

the coefficient of CO₂ emissions is -0.1765, which means when CO₂ emissions decreases by 1%, forest productivity will increase by 0.1765%. That is, reducing CO₂ emissions can effectively improve forest productivity. This also means that reducing CO₂ emissions has important practical significance for China. By reducing CO₂ emissions, it will not only help China achieve its goal of carbon neutrality, but also help China increase forest productivity. The coefficient of economic loss is -0.0116, which means economic loss will reduce forest productivity. CO₂ emissions will bring about the greenhouse effect, making the temperature rise. Rising temperature will cause insect infestation, which will affect and reduce forest productivity. In addition, CO₂ emissions will cause bad weather, drought, rain and other natural disasters. These natural disasters will directly and indirectly bring economic loss and thus reduce forest productivity. Therefore, in order to increase China's forest productivity, it is necessary to reduce CO₂ emissions and economic loss. The coefficient of technical innovation was

significantly positive. Increasing technical innovation by 1 percentage point will increase forest productivity by 0.1206 percentage points. Therefore, in order to improve forest productivity, we should further improve technical innovation, expand R&D investment, improve the quality and efficiency of forestry production by improving technical innovation, and effectively enhance forestry output.

CO₂ emissions had the greatest impact on forest productivity in west China, followed by east China, which suggests that reducing CO₂ emissions in west China was the most important among the three regions studied. CO₂ emissions in west China was the highest among the three regions, so it is particularly urgent to reduce emissions there. Meanwhile, among the three regions, only the coefficient of economic loss in west China was significantly negative. Decreasing economic loss in west China by 1 percentage point will increase forest productivity by 0.0232 percentage point. Although the coefficients of technical innovation in east and west China were both positive, that in east China did not pass significance test. The coefficient of technical innovation in west China was significantly positive. Therefore, it is of great significance to improve R&D investment in west China to improve local forest productivity. The coefficients of SE in east and middle China were significantly negative. Second industry consumed a large amount of fossil energy such as coal and oil, and contributed a lot to CO₂ emissions. Therefore, the rise of the proportion of secondary industry would reduce forest productivity.

Conclusions and Implications

Conclusions

This study measures forest productivity and empirically validates the impacts of CO₂ emissions and economic loss on forest productivity using panel data on 30 Chinese provinces from 2004 to 2020. Our major conclusions are: First, full panel mean group estimation showed that CO₂ emissions had significant negative impacts on forest productivity in China. Second, the coefficient of economic loss was significantly negative, which means reducing economic loss can increase forest productivity. Technical innovation exerted positive impacts on forest productivity, whereas industrial structure had negative impacts on it. Furthermore, regional heterogeneity analysis indicates that CO₂ emissions in west China had the greatest impact on forest productivity, followed by east China. The coefficients of economic loss in west, east and middle China were all negative, with those in east and middle China not passing significance test. The decrease of economic loss in west China effectively increased forest productivity. The coefficients of technical innovation in east and west China were both positive, while that in east China did not pass significance test. The coefficient

of technical innovation in west China was significantly positive, which means the improvement of technical innovation in west China would significantly increase forest productivity. The coefficients of industrial structure in east and middle China were significantly negative, which means increasing the proportion of secondary industry could decrease forest productivity.

Policy Implications

We put forward the following policy implications based on empirical results to improve forest productivity:

First of all, efforts should be made to lower CO₂ emissions. According to empirical estimation results, reducing CO₂ emissions is an important way to increase forest productivity. In order to reduce CO₂ emissions, China has pledged to realize carbon peaking, carbon neutrality, established "1+N" policy systems, and implemented new-type urbanization and other measures. Notably, existing studies have shown that increasing forest area and intensifying forestry investment can reduce CO₂ emissions. Therefore, we can resort to afforestation to expand forest area and improve carbon sink capacity [53]. In addition, we should strengthen forest ecological construction and improve forest quality. Furthermore, it is necessary to expand financial investment in forest and grass industries based on regional conditions. West China owns the most abundant forest resources, so CO₂ emissions has the greatest impacts on forest productivity. Parties concerned should increase forestry investment and shift the focus from resource endowment to CO₂ emissions reduction to reduce CO₂ emissions and increase forest productivity simultaneously.

Secondly, endeavors should be made to reduce economic loss caused by factors such as environmental pollution, natural disasters, geological disasters and forest fires. While reducing environmental pollution, it is necessary to build more disaster prevention and mitigation infrastructure, including strengthening early warning and response to natural disasters and improving capabilities to withstand them to minimize economic loss caused by them. Local governments at all levels should add the negative growth of geological disasters to their task list and strive to effectively prevent and control geological disasters and realize sustainable forestry development. More efforts should be made to prevent forest fires, as with other disasters, which should be supplemented by control measures. The system of local administrative heads taking responsibility should be adopted. It is also necessary to establish forest and grassland fire prevention and control command agencies at all levels and strengthen the capabilities of comprehensive national fire rescue teams.

Thirdly, technical innovation should be improved. Technical innovation can not only reduce forestry investment and increase forest productivity directly, but also helps reduce CO₂ emissions and economic loss. Thus, all regions should enhance R&D investment

and improve technical innovation. West China made the least investment in R&D among the three regions, but has the biggest strength to improve forest productivity, so it should particularly increase investment in R&D to maximize the positive impact of forest productivity. In addition, scientific and technological cooperation between the eastern and the western regions can be carried out to promote collaborative innovation. Among the three regions, the eastern region has the highest level of technological innovation, so the eastern region can provide technical support to the western region and improve the scientific and technological innovation capacity of the western region.

Finally, endeavors should be made to upgrade industrial structure. Rising the proportion of secondary industry will reduce forest productivity, so it is necessary to upgrade industrial structure. Parties concerned should vigorously develop green and low-carbon industries and adopt a green and low-carbon production and lifestyle. Clean energy and renewable energy should be applied in production and life. Coal and clean energy should be used in an environment-friendly way so as to reduce CO₂ emissions while increasing forest productivity.

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Conflicts of Interest

The authors declare no conflict of interest.

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