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China's Climate Change Policy Attention and Forestry Carbon Sequestration Growth

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Abstract: Forest carbon sinks play an important role in climate change mitigation and adaptation. The Chinese government has demonstrated its proactive approach to addressing climate change by setting development targets for low-carbon transformation and making solemn commitments to peak carbon emissions before 2030 and to achieve carbon neutrality by 2060. In this article, the Chinese Government's Work Reports and Five-Year Plans are used to construct an index named China's Climate Change Policy Attention (*CCPA*), which reflects the government's emphasis on climate change and forestry in China. This article aims to examine the impact of *CCPA*, the adjusted Climate Policy Uncertainty (*CPU*) index from the U.S., and the Economic Policy Uncertainty (*EPU*) index from China on the Chinese forest carbon stocks (*FCS*) comprehensively. On this basis, we are interested in clarifying the channels by which *CCPA* promotes the growth of forest carbon sequestration in China. Specifically, panel data from 30 provinces in China from 2000 to 2017 are used for empirical analysis, and the following results are obtained: (1) The baseline regression indicates that *CCPA* significantly promotes the growth of *FCS*, while *CPU* or *EPU* inhibits its growth. (2) The interactive regression shows that the effect of *CCPA* on the growth of *FCS* can mitigate the inhibiting impact of *CPU* or *EPU*. (3) Mediation analysis documents that *CCPA* promotes *FCS* growth by increasing the forest tending area, expanding the existing forest area, increasing renewable energy consumption, and improving green investment. (4) Heterogeneity analysis reveals a clear differentiation in the effect of *CCPA* on *FCS* under different situations. Finally, policy implications are proposed based on the results. This article is expected to provide a theoretical basis for the Chinese government to develop relevant policies from the perspective of promoting *FCS* growth.

Keywords: climate change; policy attention; carbon stock; forestry carbon sequestration; channels analysis

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1. Introduction

The Chinese government has always attached great importance to climate change and has taken proactive measures to mitigate and adapt to it. Forest carbon sinks are regarded as one of the most cost-effective means of tackling climate change [1], and the Chinese government has made forest carbon sequestration a national strategy to address climate change. In September 2020, at the 75th session of the United Nations General Assembly, China announced its commitment to improve its nationally determined contributions (NDCs) and adopted more vigorous policies and measures, with goals related to peak carbon dioxide emissions before 2030 and achieving carbon neutrality before 2060. In the same year, at the Climate Ambition Summit, China also promised to increase forest volumes by 6 billion cubic meters from 2005 levels by 2030. In October 2021, China submitted its "China's Achievements, New Goals, and New Measures for Nationally Determined

Contributions", which reaffirmed the overall targets of peak carbon emissions before 2030 and achieving carbon neutrality by 2060, with a 65% reduction in carbon intensity per unit of gross domestic product (GDP) by 2030 compared to 2005. It could be seen that forest carbon stocks (FCS) will play an irreplaceable role in achieving the carbon peak and carbon neutrality targets as scheduled [2]. Therefore, achieving stable and rapid growth of FCS is of great importance for China to realize sustainable development.

There is a growing body of literature on the promotion of FCS growth. For example, some scholars have quantitatively identified the relationship between institutional freedom and FCS growth [3,4]. Ge and Lin [5] examined the relationship between the signing of the Kyoto Protocol and FCS. Zhao et al. [6] compared the interregional spillover effects of FCS in China from the perspectives of the natural environment, economic development, forest management, and environmental regulation. Most of the studies mentioned above examined the specific factors influencing the growth of FCS and provided policy implications. The aim is to encourage all levels of government to pay more attention to the effective approaches to using FCS to tackle climate change.

Therefore, promoting the growth of FCS becomes an important pathway to achieving carbon neutrality, and it is also expected to experience a rapid growth due to China's climate change policy attention ($CCPA$). However, since the U.S. is the largest economy in the world, its climate policy uncertainty (CPU) can affect other countries and regions to a large extent. In addition, increasing economic policy uncertainty (EPU) in China may lead local governments to prioritize short-term GDP growth targets over long-term green transformation goals, which is also detrimental to the growth of FCS.

However, there is limited research available on the specific effects of $CCPA$ on FCS, and the interactive effects of $CCPA$ with CPU or EPU on FCS. The channels through which $CCPA$ grows FCS and whether the effect of $CCPA$ on FCS varies under important different conditions are also not well studied in the existing literature. Answers to these great issues would provide valuable insights into China's low-carbon development, promote the growth of FCS and the development of relevant industries, and help to achieve the carbon peak and carbon neutrality targets as planned.

The marginal contributions of this article are as follows: First, it synthesizes the $CCPA$ index that comprehensively reflects the government's attention to climate change and forestry. Second, it empirically tests the effect of $CCPA$, CPU and EPU on FCS, respectively, and the interactive effects of $CCPA$ with CPU or EPU. Next, it theoretically clarifies the underlying mechanisms through which $CCPA$ affects FCS and explores four potential pathways. Finally, it empirically analyzes the differences in the effects of $CCPA$ on FCS in different regions (Based on the different levels of economic development, China can be divided into two major regions: the east and middle regions, representing higher economic development, and the west region, representing relatively less-developed economic development. See Section 5.1.1 for more details about division of provinces), different forest regions (China has three major forest regions: the northeast forest region, the southwest forest region, and the southern collective forest region. Based on the different origins of the forests, the provinces in the northeast forest region and the southwest forest region are classified as natural forest regions, while the provinces in the southern collective forest region are classified as artificial forest regions), and different numbers of pollutant discharge permit enterprises.

The remainder of this article is organized as follows: Section 2 develops the research hypotheses. Section 3 describes the empirical design and data. Section 4 discusses the empirical results and conducts channel analysis and robustness tests. Section 5 involves further exploration based on a heterogeneity analysis. Section 6 is the discussion of this article. Section 7 provides the conclusions and implications.

2. Hypothesis Development

2.1. The Theoretical Analysis of Factors Affecting FCS

2.1.1. The Impact of *CCPA* on *FCS*

There is little research on the influence of *CCPA* on *FCS* in the existing literature. However, the relevant literature has confirmed that the policy documents on climate change issued by the Chinese government have a positive impact on *FCS* [6–11]. The successive release and implementation of the above policy documents are inseparable from the Chinese government's attention to climate change and forestry (*CCPA*). That is, the influence of the relevant policy documents on *FCS* can indeed reflect the effect of *CCPA* on *FCS* to some extent. Based on the above, we believe that there is indeed a certain causality between *CCPA* and *FCS* (*CCPA*, policy documents, and policy implementation are not substitutive in this article. *CCPA*, as the embodiment of government consciousness, can guide the formulation of policy documents, and policy documents can guide the specific actions of policy implementation. To be specific, policy documents and policy implementation are the concretization of *CCPA*. In this article, we mainly focus on the impact of *CCPA* on *FCS*). For example, the National Development and Reform Commission (NDRC) issued the "Opinions on Implementing the Strategy of Main Functional Zones and Promoting the Construction of Main Functional Zones" in 2013, which explicitly stated the priority of including forestry carbon sinks in key ecological functional areas into the pilot carbon emissions trading program. The State Forestry Administration of China issued the "Key Points of Forestry Action for Climate Change during the 13th Five-Year Plan" in 2016, which explicitly outlines targets such as increasing forest carbon sinks, reducing forestry emissions, and enhancing the adaptive capacity of forestry. Zhao et al. [6] found in their study that the carbon emissions trading pilot policy can promote the growth of local forest carbon sinks, and environmental regulations can have positive spillover effects on neighboring areas. Yuan et al. [7] showed in their study that managing degraded bamboo forests helps to restore their carbon sequestration capacity. Daigneault et al. [8] confirmed the significant role of forest management and carbon pricing in increasing *FCS*. Liu et al. [9] found that appropriate forest thinning promotes forestry carbon sequestration and environmental protection. These studies all incline toward indicating that *CCPA* has a positive effect on *FCS* to some extent.

In addition, since the beginning of the 21st century, the Chinese government has implemented six major forestry ecological projects through policy documents to use forestry to tackle climate change. These projects include natural forest protection, Three-North and the Middle and Lower Reaches of the Yangtze River Shelterbelt Construction, Green for Grain project, Wind and Sand Source Area Control Around Beijing and Tianjin, Wildlife Protection and Nature Reserve Development, as well as the Fast-Growing and High-Yielding Timber Base Construction Program in Key Areas. These initiatives have promoted the expansion of forest areas and the increase of forest carbon sinks [10,11].

2.1.2. The Impact of *CPU* on *FCS*

As the world's largest economy, the U.S. has the ability and responsibility to join other countries in addressing the increasingly serious problem of global warming. However, the wavering position of the U.S. on climate policy has been the subject of controversy. Gavriilidis [12] proposed an index called *CPU* to measure climate policy uncertainty in the U.S. Numerous studies have shown that *CPU* is not conducive to controlling global climate change and the protection of forests. The existing literature on *CPU* mainly focuses on its effect on renewable energy consumption, which is closely related to carbon emissions. For example, Guo et al. [13] examined the significant impact of *CPU* on global crude oil and natural gas prices. Shang et al. [14] quantitatively analyzed the impact of *CPU* on renewable and non-renewable energy consumption, based on data from the first quarter of 2000 to the third quarter of 2023 in the U.S. The results showed that *CPU* reduces the demand for non-renewable energy but increases the consumption of renewable energy. Li et al. [15] investigated the effects of *EPU* and *CPU* on renewable and non-renewable energy consumption. The results showed that in most periods, *EPU* suppresses renewable energy consumption and stimulates non-renewable energy consumption. *CPU* always stimulates an increase in non-renewable energy consumption, but its influence on renewable energy consumption depends on the government's positive or negative attitudes toward climate change. Lin and Zhao [16] argued that an increase in *CPU* leads to an increase in fossil fuel consumption, resulting in an increment in carbon emissions. In addition, scholars have conducted some studies on the direct causal relationship between *CPU* and carbon dioxide emissions. For example, Zeng et al. [17] found that the U.S. climate policy uncertainty index contains more relevant information for carbon neutrality and can influence the Carbon Neutrality Concept index constructed using the China A-share index in the Wind Financial Terminal. Guesmi et al. [18] measured climate risk in terms of financial costs and fatalities from natural disasters and calculated the *CPU* index using the method proposed by Gavriilidis [12]. They examined the impact of climate risk and *CPU* in the U.S. from 2000 to 2022 on carbon dioxide emissions. The results showed that both climate risk and climate policy uncertainty have a significant impact on carbon emissions. Effective control of *CPU* can reduce various types of emissions, highlighting the need for the U.S. to unify its policy direction and strengthen its response to global climate change. These studies are inclined to conclude that *CPU* is harmful to the ecological environment, focusing on the direct or indirect effects on carbon dioxide emissions. Since *CPU* has a negative impact on the ecological environment, it is also not conducive to increasing forest carbon sinks theoretically.

2.1.3. The Impact of *EPU* on *FCS*

The negative impact of *EPU* on the ecological environment has been proved in many studies, but they often focus on its effects on carbon emissions or the eco-footprint (EF), with less attention given to its impact on *FCS*. On the one hand, a significant amount of research used the EF as a characterization of ecological degradation and investigated the relationship between *EPU* and EF. For example, Xu et al. [19] empirically tested the relationship between natural resources, economic policy uncertainty, energy structure, and EF, confirming the negative impact of *EPU* on the eco-environment. Hussain et al. [20] used the stochastic impacts by regression on population, affluence, and technology to study the impact of *EPU*, environmentally related technologies, and renewable energy consumption on the eco-environment. The results showed that *EPU* led to an increase in EF, while environmentally related technologies and renewable energy consumption led to a decrease in EF. On the other hand, some studies use carbon dioxide emissions as a measure of the ecological environment and investigate the relationship between *EPU* and carbon emissions (CE) or carbon intensity (CI). For instance, the study of Zhou et al. [21] indicated that *EPU* exacerbated CE in both the long and short term, indicating that *EPU* deteriorated the ecological environment. Yu et al. [22] empirically analyzed the impact of *EPU* on CI. The results showed that *EPU* led to a significant increase in CI. Further channel analysis revealed that enterprises tend to choose cheap and dirty fossil fuels to cope with the increasing business risks caused by *EPU*, exacerbating the burden on the ecological environment. The above studies demonstrated the negative impact of *EPU* on the ecological environment through indicators such as eco-footprint, carbon emissions, and carbon intensity. However, there is limited literature that considered *FCS* as a measure of the eco-environment and investigated its relationship with *EPU*. Based on the above review, we suppose that China's *EPU* will decrease *FCS*.

Based on the comprehensive analysis of the three aspects mentioned above, the first hypothesis of this article is proposed:

H1: The *CCPA* can significantly increase China's *FCS*, yet factors such as *CPU* in the U.S. and *EPU* in China will hinder the growth of *FCS*.

2.2. The Interaction Effect between CCPA and CPU or EPU

CCPA, the release of climate policy documents, and the implementation of climate policy form an evolution process of interlinked cycle. *CCPA* can guide the formulation of climate policy documents, and these policy documents can further transform the specific actions of climate policy implementation, such as a series of measures to protect forest resources, including quota-based logging, protection of natural forests, afforestation, closing hillsides to facilitate afforestation, returning farmland to forests, and expansion of forest cover [2,23,24]. Furthermore, based on the actual effects of climate policy implementation, the government will gradually update and adjust the policy documents to continuously optimize and improve them in the formulation and implementation process, to better address climate change. Specifically, although *CPU* and *EPU* are not expected to be conducive to the growth of *FCS*, under the positive influence of *CCPA*, the government has to consider how to prevent the potential adverse impacts of *CPU* or *EPU*. Then, the government is allowed to gradually address the impacts of *CPU* and *EPU* on forest carbon sinks through continuously optimizing its climate policies. It is generally assumed that a country's increasing attention to climate change and forestry issues (*CCPA*) is usually accompanied by the implementation of strict policies to reduce greenhouse gas emissions and improve environmental protection and governance [6,25]. Due to the important role of forestry in mitigating and adapting to climate change [1], as well as the Chinese government's high regard for the development of *FCS* [2], thus, under the drive of carbon peak and carbon neutrality targets, it is expected that the Chinese government will take decisive and effective measures to overcome the negative impact of *EPU* and *CPU* on *FCS*. Therefore, we expect that the positive effect of *CCPA* will mitigate the negative impact of *EPU* or *CPU* on the growth of *FCS*. Then, the second hypothesis of this article is proposed:

H2: *CCPA* promotes *FCS* growth and can effectively counteract the negative effects of *CPU* in the U.S. or *EPU* in China on *FCS* growth.

2.3. Channels to the Impact of CCPA on FCS

2.3.1. Forest Tending Area

We suppose that *CCPA* can promote the growth of *FCS* by the channel of increasing the forest tending area. This supposition is mainly based on the following considerations. First, *CCPA* promotes the expansion of the forest tending area. The Chinese government has made solemn commitments in the world to increase forest volume and forest area. At the same time, the Chinese government is actively implementing a series of forest conservation and ecological restoration projects, such as forest closure, returning farmland to forest and the Three-North Shelterbelt Program [26]. These efforts will inevitably promote the expansion of the forest tending area. Second, the increase in the forest tending area can promote the growth of *FCS* [27]. According to the current methodologies of forest carbon sequestration projects, the increase in *FCS* can be realized through two methods: management carbon sequestration and afforestation carbon sequestration [2,28–30]. The management carbon sequestration corresponds to an increase in the forest tending area.

2.3.2. Forest Area

The effect of increasing forest area on *CCPA* influence on *FCS* is akin to that of increasing forest tending area. That is, *CCPA* can also promote the growth of *FCS* by the channel of expanding the forest area. Due to the government's attention to climate change and forestry that the government has promoted, the implementation of a series of actions, such as returning farmland to forest, limiting forest logging, and afforestation, have promoted the expansion of the forest area. A lot of the literature points out that the expansion of the forest area is one of the important reasons for the increase in *FCS* [2–4].

2.3.3. Renewable Energy Consumption

We expect that *CCPA* can promote the growth of *FCS* by the channel of encouraging the consumption of renewable energy. As the government's attention to climate change and forestry increases, there will inevitably be strict control of carbon emissions while promoting the consumption of renewable energy and curbing the consumption of non-renewable energy [31–33]. In addition, the increase in renewable energy consumption will contribute to the growth of *FCS*. For example, the use of deadwood and forest residues as renewable energy for combustion or power generation can not only meet the growing demand for energy consumption but can also reduce the risk of forest fires to some extent [33], thereby preventing carbon leakage from forests and promoting the growth of *FCS*.

2.3.4. Green Investment

We suppose that *CCPA* can promote the growth of *FCS* by the channel of improving the level of green investment. On the one hand, *CCPA* can promote the development of green investment while increasing the consumption of renewable energy [34,35]. On the other hand, the development of green investment has a positive impact on the growth of *FCS* [7,36]. For example, the emergence and development of green finance investments, such as forest rights pledge loans, forest carbon sequestration revenue rights pledge loans, China Green Carbon Foundation, forestry carbon sequestration insurance, and carbon subsidies, have reduced the financing pressure on forestry carbon sequestration projects, thereby promoting the development of forestry carbon sequestration and related industries, as well as the growth of *FCS* [7,36].

Then, the third hypothesis of this article is proposed:

H3: *CCPA* can promote the continuous growth of *FCS* in China by increasing the forest tending area (*TA*), the forest area (*FA*), renewable energy consumption (*REC*), and green investment (*GI*).

3. Empirical Design

3.1. Variables Selection

3.1.1. Dependent Variables

(1) Forest Carbon Stocks Based on Forest Biomass–Age Relationships

The existing literature has accumulated a certain amount of research on the calculation of forest carbon stocks [37–39]. We adopt two authoritative indicators, called *FCS*1 and *FCS*2, to represent forest carbon stocks. *FCS*1 is based on the research approach introduced by Xu et al. [37]. We use their estimated carbon density for existing forests and newly planted forests in China in the year 2000 to derive the forest carbon stock data for 30 provinces in mainland China (excluding Tibet) from 2000 to 2017. The specific calculation process is listed in Equations (S1)–(S3).

(2) Forest Carbon Stocks by Estimating Remote Sensing Observations

The data for *FCS*2 are derived from Chen et al. [38,39], who conducted field measurements of aboveground biomass carbon stocks (AGBC) in 2444 ground sample plots across the country from 2002 to 2021. They also created a random forest model to predict the belowground biomass carbon stocks (BGBC) using observations from 8729 forest sample plots nationwide. The data resolution is 1×1 km. First, we use ArcGIS 10.5 software to calculate the average carbon density of AGBC and BGBC for 30 provinces. Second, the forest area of each province is multiplied by the respective average carbon densities of AGBC and BGBC to obtain the aboveground and belowground biomass carbon stocks. The two values are then added together to get the forest carbon stock data. Last, a three-year moving average method is used to fill in the missing data for the years 2000–2001. The specific calculation procedure is listed in Equation (S4).

3.1.2. Independent Variables

(1) China's Climate Change Policy Attention

The Chinese Government's Annual Work Reports and Five-Year Plans outline the government's summary of past work and outlook for future blueprints and reflect the government's attention to economic and social activities to a great extent. To select vocabularies that reflect the government's focus on climate change and forestry, we adopt the approach of Baker et al. [40] and consider the unique context of China. The specific procedure is as follows: First, a manual review of the Chinese Government's Annual Work Reports and Five-Year Plans from 2000 to 2017 is conducted to identify high-frequency vocabularies related to the government's focus on climate and forestry. Examples of such vocabularies in the policy documents include nationally determined contributions, greenhouse gases, carbon neutrality, carbon sinks, returning farmland to forests, closing hillsides to facilitate afforestation, and so on, for a total of 62 terms. All of them reflect the government's attention to climate change and its determination to utilize forestry in addressing climate change. Second, we use Python 3.9 software to analyze the frequency of words based on the provincial government work reports from 2000 to 2017. The frequency and total number of words of the high-frequency vocabularies related to climate and forestry in the provincial government work reports are calculated. Due to missing government work reports for certain years in some provinces, the missing values are filled using a three-year moving average method. Third, to ensure consistency, the proportion of high-frequency vocabularies in the total number of words in the full text was used as a proxy for government attention to climate change and forestry. The higher the proportion, the higher the indirect indication of the government's attention to climate and forestry [41].

(2) Climate Policy Uncertainty in the U.S.

We evaluate the impact of U.S. climate policy uncertainty on FCS for the following reasons: One of the concerns of this article is the negative impact on FCS derived from climate policy uncertainty. China has been trying to show the outside world its determination to address climate change, so the Chinese central government has always been highly concerned about all aspects of climate change issues, and its climate policies can be considered more predictable, at least at the central government level. In contrast, the U.S. federal government has been inconsistent in its stance on dealing with climate change due to the rotation of political parties. This has resulted in a considerable level of uncertainty in the U.S. government's climate policies. What is more, as the U.S. is the largest economy in the world, its attitude toward climate change influences global climate governance to a great extent. Naturally, climate policy uncertainty in the U.S. can also affect the economic and social development of an export-oriented economy like China [42]. We use the index proposed by Gavriilidis [12] to measure climate policy uncertainty in the U.S., which has already been used by scholars to assess its impact on China's economic and social development, such as firm's performance [42], green innovation [43], stock markets [44], and so on. However, the index is time series data, and it cannot reflect the impact on each province in China. To address this and establish panel data, we adjust the CPU using each province's share of total imports and exports since China's economic growth relies on international trade to a large extent. CPU is adjusted as follows:

$$Adjusted\ CPU_{it} = CPU_t \times \frac{IMEX_{it}}{TIMEX_t} \tag{1}$$

where subscripts i and t in the equation represent the province and year, respectively. Adjusted CPU represents the adjusted climate policy uncertainty index, where CPU is the climate policy uncertainty index for the U.S. $IMEX$ represents the total import and export value of each province. $TIMEX$ represents the national total import and export value, which is the sum of the import and export values of 30 sample provinces in this article. For the sake of brevity, the term "$Adjusted\ CPU$" will be referred to as "CPU" in the following text, unless otherwise stated.

(3) China's Economic Policy Uncertainty

We directly use the provincial economic policy uncertainty index calculated by Yu et al. [22], which was derived from word frequency statistics based on daily newspapers for each province from 2000 to 2017. The relevant high-frequency words related to economic policy uncertainty about China that Yu et al. [22] used in synthesizing this index were selected from the Chinese Government's Work Reports and Five-Year Plans of the Chinese central government over the past fifty years. Compared to Baker et al.'s [40] economic policy uncertainty index for China, which is time series data, the index used in this article is more comprehensive and reliable [22] and can reflect the heterogeneity across the provinces. As mentioned in Yu et al. [22], Baker et al.'s index of China's EPU tends to understate or even distort economic policy uncertainty in China.

3.1.3. Control Variables

Following the approach of the current literature [3–5], the following variables are controlled in the baseline model: logarithm of per capita GDP ($GDPP$); agricultural value added ($AGRI$); industrial value added ($INDU$); service industry value added ($SERV$); and urbanization rate ($URBA$), represented by the proportion of urban population at the end of the year. The GDP growth rate ($GDPG$) and population growth rate ($POPG$) are measured as Equations (2) and (3), respectively. Forest coverage rate ($COVER$); openness ($OPEN$) is measured by the ratio of total import and export value to nominal GDP, and the energy structure ($STRUC$) is measured by the ratio of renewable energy consumption to total energy consumption. The calculation of renewable energy consumption refers to the method of Destek and Aslan [45] and Wang et al. [46], using electricity generation from renewable sources, such as hydro, wind, solar, and nuclear. Other controlled variables include a dummy variable of pilot carbon market ($TRADE$), forest pest control area ($PEST$), the logarithm of forestry investment ($INVEST$), the relationship between government and market (GOV_MKT), and the development of the non-state sector ($NONSTATE$) derived from the subindices of the Fan Gang Index [47] in the Wind Financial Terminal.

$$GDPG_{it} = \frac{GDP_{it} - GDP_{i,t-1}}{GDP_{i,t-1}} \tag{2}$$

$$POPG_{it} = \frac{POPU_{it} - POPU_{i,t-1}}{POPU_{i,t-1}} \tag{3}$$

where $GDPG$ and $POPG$ are the growth rate of GDP and total population ($POPU$), respectively.

3.1.4. Other Important Variables

(1) Intermediate Variables

We mainly select the following four intermediate variables, which include three types: (1) forest tending area (TA) and forest area (FA). According to the growth mechanism of forest carbon sinks, the current methodology for forest carbon sink projects in China distinguishes between afforestation carbon sinks and management carbon sinks. On the one hand, given the strict restrictions on forest harvesting in China, an increase in afforestation areas inevitably leads to an increase in forest area, which is closely related to the growth of forest carbon sinks. Forest tending is one of the most important forest management practices and an important pathway to increase forest carbon sinks. On the other hand, increasing forest carbon sequestration is one of the cost-effective measures to address climate change [48]. The increase in $CCPA$ will inevitably lead to an increase in TA and FA. Therefore, this article selects the TA and FA as intermediate variables. It should be noted that the data on TA may be missing in some years and provinces, and the three-year moving average method is used to fill it. (2) Renewable energy consumption (REC). On the one hand, the use of deadwood and residual materials from forest harvesting as renewable energy for combustion or power generation can not only meet the growing demand for energy consumption but can also reduce the risk of forest fires to some extent [33], thereby avoiding forest carbon leakage and promoting the growth of FCS to some extent. On the other hand, with the increasing $CCPA$, the government will tighten carbon emission regulations, encourage an increase in the consumption of renewable energy, and discourage the consumption of non-renewable energy sources, such as fossil fuels. Renewable energy consumption is calculated as mentioned above. (3) Green investment (GI), whose measurement is based on Chen [49], measures and normalizes the ratio of environmental protection investment to GDP.

(2) Instrumental Variable

We choose the logarithmically transformed average wind speed ($WIND$) as an instrumental variable to cope with the endogeneity of $CCPA$ in Equation (4) in Section 3.2.1. On the one hand, there is no evidence indicating that average wind speed could directly affect forest carbon stocks. On the other hand, average wind speed is closely related to $CCPA$ [50]. In regions with slower wind speeds, the diffusion rate of greenhouse gases is slower, leading to higher gas concentrations and a more pronounced greenhouse effect. Therefore, it is reasonable to believe that $CCPA$ is higher in regions with slower wind speeds.

3.2. Regression Models Specification

3.2.1. Baseline Model

Referring to Lin and Ge [4], three baseline panel regression equations are employed, using a two-way fixed-effects model as follows:

$$FCS_{it} = \alpha_1 + \beta_1 CCPA_{it} + \gamma_1 Controls + \delta_i + \mu_t + \varepsilon_{it} \tag{4}$$

$$FCS_{it} = \widetilde{\alpha}_1 + \widetilde{\beta}_1 CPU_{it} + \widetilde{\gamma}_1 Controls + \widetilde{\delta}_i + \widetilde{\mu}_t + \widetilde{\varepsilon}_{it} \tag{5}$$

$$FCS_{it} = \overline{\alpha}_1 + \overline{\beta}_1 EPU_{it} + \overline{\gamma}_1 Controls + \overline{\delta}_i + \overline{\mu}_t + \overline{\varepsilon}_{it} \tag{6}$$

where the tildes and bars are used to distinguish the coefficients in different equations. FCS is the dependent variable in this article, and two different sources of forest carbon stocks are used, referred to as $FCS1$ and $FCS2$. The article selects three independent variables in the baseline regressions: $CCPA$, CPU, and EPU. The regression coefficients β_1, $\widetilde{\beta}_1$ and $\overline{\beta}_1$ reflect the extent to which these independent variables affect China's FCS. $Controls$ is the vector of control variables introduced into the regression equation, and the vector of regression coefficient is recorded as γ_1, $\widetilde{\gamma}_1$, and $\overline{\gamma}_1$, respectively. The intercept coefficient of the regression is recorded as α_1, $\widetilde{\alpha}_1$, and $\overline{\alpha}_1$, respectively. δ_i, $\widetilde{\delta}_i$, and $\overline{\delta}_i$ are the province-fixed effect, μ_t, $\widetilde{\mu}_t$ and $\overline{\mu}_t$ are the year-fixed effect, and ε_{it}, $\widetilde{\varepsilon}_{it}$, and $\overline{\varepsilon}_{it}$ are the random error term.

3.2.2. Interaction Effects Model

Having clarified the impact of the three independent variables on FCS, we will examine the interaction effects of $CCPA$ with CPU or EPU separately to determine whether $CCPA$ plays a dominant role in the growth of China's FCS. Referring to Giesselmann and Schmidt-Catran [51], the regression equations for the relevant interaction effects are as follows:

$$FCS_{it} = \varphi_0 + \varphi_1 CCPA_{it} + \varphi_2 CPU_{it} + \varphi_3 CCPA_{it} \times CPU_{it} + \varphi_4 Controls + \delta_i + \mu_t + \varepsilon_{it} \tag{7}$$

$$FCS_{it} = \omega_0 + \omega_1 CCPA_{it} + \omega_2 EPU_{it} + \omega_3 CCPA_{it} \times EPU_{it} + \omega_4 Controls + \delta_i + \mu_t + \varepsilon_{it} \tag{8}$$

The two regression equations include two independent variables and the interaction terms of $CCPA$ with CPU or EPU. φ_3 and ω_3 represent the effect of the interaction terms on FCS, respectively. The regression controls for province- and year-fixed effects.

3.2.3. Mediation Effects Model

Next, the mediation effects model is used to test the channels that influence China's *FCS*. Referring to Jiang [52], two additional regression equations are added to the baseline model Equation (4) to form a three-stage regression model to test the mediation effects:

$$M_{it} = \alpha_2 + \beta_2 CCPA_{it} + \gamma_2 Controls + \delta_i + \mu_t + \varepsilon_{it} \tag{9}$$

$$FCS_{it} = \alpha_3 + \beta_3 CCPA_{it} + \eta M_{it} + \gamma_3 Controls + \delta_i + \mu_t + \varepsilon_{it} \tag{10}$$

The mediating variables M_{it} used in our article are TA, FA, REC, and GI, in turns. The steps to test the mediation effects are as follows: test the significance of β_1 or β_2. If all of them are significant, then the significance of η is tested. A significant η indicates the presence of a mediating channel that explains the positive impact of China's continuous improvement in $CCPA$ on FCS. If β_1 is significant and either β_2 or η is not significant, further clarification of the existence of the mediating effect is required through the Sobel test [52]. The basic principle of the Sobel test is to examine the significance of $\beta_2 \times \eta$, which represents the indirect effect of M_{it}. A significant $\beta_2 \times \eta$ stands for the presence of a mediating effect.

3.2.4. Heterogeneity Testing Model

Heterogeneity testing in our article is carried out using two approaches: subsample regression and threshold regression. First, the sample was divided into subsamples based on different regions and different forest regions, and regression was performed on each subsample to test for regional heterogeneity. The regression equation used to test for subsample heterogeneity is the same as model (4), which will not be repeated here.

Referring to Lin and Ge [4], a threshold effect regression model is then employed to analyze the impact of $CCPA$ on FCS in the heterogeneity analysis of different numbers of pollutant discharge permit enterprises:

$$\begin{aligned} FCS_{it} = {} & \theta_0 + \theta_1 CCPA_{it} \times I(P_{it} \le M_1) + \theta_2 CCPA_{it} \times I(M_1 < P_{it} \le M_2) \\ & + \theta_3 CCPA_{it} \times I(M_2 < P_{it} \le M_3) \\ & + \theta_4 CCPA_{it} \times I(M_3 < P_{it} \le M_4) + \theta_5 CCPA_{it} \times I(P_{it} > M_4) \\ & + \theta_6 Controls + \mu_t + \varepsilon_{it} \end{aligned} \tag{11}$$

where P_{it} is the number of pollutant discharge permit enterprises in province i in year t. θ_1, θ_2, θ_3, θ_4, and θ_5 represent the impact of $CCPA_{it}$ on FCS_{it} when P_{it} falls within the intervals $(0, M_1]$, $(M_1, M_2]$, $(M_2, M_3]$, $(M_3, M_4]$, and (M_4, ∞), respectively. $I(\cdot)$ is an indicator function, which equals 1 if the condition in the brackets is true and 0 otherwise. For example, when P_{it} falls within the interval $(0, M_1]$, then θ_1 equals 1, and θ_2, θ_3, θ_4, and θ_5 all equal 0. μ_t represents the year-fixed effect, and ε_{it} represents the random error term.

3.3. Sample and Descriptive Statistics

The sample constructed in this article consists of panel data from 30 provinces (excluding Tibet) in mainland China from 2000 to 2017. The data includes variables such as FCS, $CCPA$, CPU, EPU, and control variables. For missing data, we use a three-year moving average method to fill them. The data for the sample are collected from various sources, including the Annual Government Work Reports of the Chinese government and provincial governments, Five-Year Plans, China Statistical Yearbook, China Forestry Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, and China Power Yearbook, among others. The descriptive statistics of variables are listed in Table 1.

Figure 1 depicts the trends of two dependent variables and the key independent variable, $CCPA$, during the period from 2000 to 2017. The values of independent and dependent variables are the average values across 30 provinces each year. It can be observed that $CCPA$, $FSC1$, and $FSC2$ exhibit similar overall trends, showing a clear upward trend from 2000 to 2017. This indicates a positive correlation between $CCPA$ and FCS, which intuitively supports the speculation in H1 of this article regarding the impact of *CCPA* on *FCS*. However, whether *CCPA* promotes the growth of *FCS* requires further verification through empirical study.

Table 1. Descriptive statistics.

Variable	Unit	Obs.	Mean	Std	Min	Max
*FCS*1	10^6 ton (CO_2)	540	2166.1933	2014.2432	5.3005	10,527.7832
*FCS*2	10^6 ton (C)	540	3900.4062	6682.9994	0.0241	31,244.1484
CCPA	%	540	0.5847	0.2654	0.0879	1.5208
CPU	I	540	3.1224	5.7675	0.0123	40.2734
EPU	I	540	0.6676	0.2372	0.0000	1.0000
GDPP	I	540	9.9796	0.8086	7.9226	11.8217
AGRI	10^8 YUAN	540	1189.3180	1037.5520	40.1000	4902.7998
INDU	10^8 YUAN	540	5801.3904	6600.8040	80.9000	39,124.1016
SERV	10^8 YUAN	540	5860.2848	6946.2369	127.6000	49,500.6992
URBA	%	540	48.3021	16.5105	15.2493	90.8602
GDPG	%	540	13.4338	5.7948	−3.9504	29.8086
POPG	%	540	3.7535	18.6849	−62.4913	283.5291
COVER	%	540	29.7356	17.6956	0.6846	66.6291
IMEX	10^8 YUAN	540	2552.9195	4957.6027	5.9727	34,027.1875
Energy	10^4 ton	540	11,043.1762	7805.2608	480.0000	38,899.0000
PEST	10^4 ha	540	18.5735	15.4812	0.0829	98.6884
INVEST	I	540	12.3665	1.4135	8.6041	15.7476
GOV_MKT	I	540	7.1929	1.8249	0.8410	12.1520
NONSTATE	I	540	7.7608	2.9440	0.6810	12.7300
TA	10^4 ha	540	21.0643	19.6143	0.1474	89.4603
FA	10^4 ha	540	646.4733	578.2976	1.8900	2588.9517
GI	I	540	0.2897	0.2338	0.0000	1.0000
RE	10^4 ton	540	274.0046	426.0570	0.0000	3215.0000
WIND	I	540	1.7289	0.1613	1.2701	2.1558

Note: The indices *CPU* and *EPU* are obtained from the previous studies conducted by other scholars; see references [12,22], respectively. These indices have been adjusted and are presented without units and are denoted by "I". The same applies to other similar indices in control and intermediate variables.

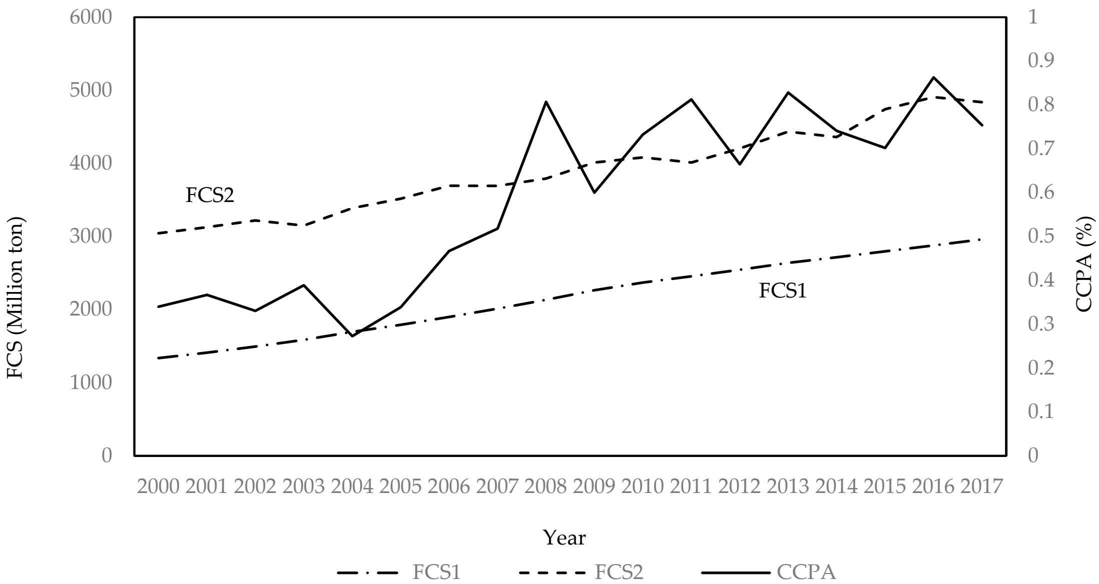

Figure 1. The trend of *CCPA* and *FCS*. The annual values of *FCS*1, *FCS*2, and *CCPA* in the picture above are all the averages across 30 provinces.

4. Empirical Results

4.1. Baseline Regression

Based on Equations (4)–(6), the baseline results are in Table 2. The first and fourth columns report the results based on Equation (4), showing the effects of $CCPA$ on FCS. Specifically, $CCPA$ significantly increases $FCS1$ and $FCS2$ at the 1% and 10% levels, respectively. The second and fifth columns present the results based on Equation (5), reporting the effects of CPU on FCS. CPU negatively affects $FCS1$ at a 5% significance level, and the coefficient on $FCS2$ is negative but not significant, consistent with our expectations regarding the sign of the regression coefficients. The third and sixth columns display the results based on Equation (6), reporting the effects of EPU on FCS. Similarly, EPU negatively affects $FCS1$ at a 5% significance level, and the coefficient on $FCS2$ is negative but not significant. In conclusion, $CCPA$ has a positive impact on FCS, while CPU or EPU has a negative impact on FCS, supporting H1. Furthermore, when regressing $FCS1$ and $FCS2$ on $CCPA$, CPU, and EPU, respectively, the magnitudes, signs, and significance levels of the control variables remain stable, indicating robust results.

Table 2. The results of baseline regression.

		***FCS*1**			***FCS*2**	
$CCPA$	379.0262 ***			525.2544 *		
	(2.9822)			(1.7847)		
CPU		−27.4578 **			−20.6022	
		(−2.1410)			(−0.6949)	
EPU			−176.6307 **			−81.3175
			(−2.1421)			(−0.4265)
$GDPP$	445.0337	622.2637	1218.1533	−2774.6877	−2418.7714	−2094.1043
	(0.4775)	(0.6675)	(1.2831)	(−1.2857)	(−1.1223)	(−0.9538)
$GDPP^2$	19.4421	18.2704	−14.3895	169.1140	161.3798	143.5558
	(0.3914)	(0.3656)	(−0.2826)	(1.4702)	(1.3970)	(1.2192)
$AGRI$	0.6870 ***	0.6458 ***	0.6671 ***	1.7008 ***	1.6509 ***	1.6640 ***
	(9.1322)	(8.6003)	(8.8889)	(9.7632)	(9.5104)	(9.5885)
$INDU$	−0.0411 **	−0.0390 **	−0.0418 **	−0.1134 **	−0.1102 **	−0.1113 **
	(−2.1385)	(−2.0221)	(−2.1608)	(−2.5513)	(−2.4737)	(−2.4906)
$SERV$	−0.0324 **	−0.0240	−0.0281 *	−0.0705 *	−0.0634 *	−0.0673 *
	(−2.0759)	(−1.4987)	(−1.7908)	(−1.9533)	(−1.7133)	(−1.8525)
$URBA$	−16.6389 ***	−16.9542 ***	−15.6540 ***	−30.3208 ***	−30.1090 ***	−29.2145 ***
	(−4.4981)	(−4.5345)	(−4.2187)	(−3.5398)	(−3.4835)	(−3.4046)
$GDPG$	−14.5312 **	−16.0700 ***	−15.2765 **	−14.6818	−16.3302	−15.7441
	(−2.4510)	(−2.6961)	(−2.5675)	(−1.0695)	(−1.1851)	(−1.1443)
$POPG$	−2.8326 ***	−2.8819 ***	−2.6648 ***	−6.7711 ***	−6.7376 ***	−6.5913 ***
	(−2.9434)	(−2.9743)	(−2.7575)	(−3.0385)	(−3.0080)	(−2.9494)
$COVER$	39.7834 ***	39.2774 ***	40.0384 ***	167.7703 ***	167.4922 ***	168.0355 ***
	(6.2596)	(6.1448)	(6.2712)	(11.3998)	(11.3350)	(11.3813)
$OPEN$	−958.7644 **	−905.1515 **	−984.5352 **	−2320.1302 **	−2278.8256 **	−2330.4253 **
	(−2.2185)	(−2.0817)	(−2.2668)	(−2.3184)	(−2.2670)	(−2.3202)
$STRUC$	560.0528 ***	526.8342 ***	528.3413 ***	1193.4390 ***	1150.4343 ***	1152.5103 ***
	(3.3482)	(3.1401)	(3.1492)	(3.0812)	(2.9661)	(2.9707)
$TRADE$	−132.2312	−115.1108	−108.4958	−530.3674 **	−499.8649 **	−493.7273 **
	(−1.3771)	(−1.1974)	(−1.1299)	(−2.3852)	(−2.2492)	(−2.2234)
$PEST$	0.4873	0.4483	0.7936	−18.8446 ***	−18.8717 ***	−18.7004 ***
	(0.1990)	(0.1822)	(0.3221)	(−3.3233)	(−3.3184)	(−3.2819)
$INVEST$	−76.2007 **	−60.3094 *	−55.9653 *	−122.6115	−98.5023	−95.5501
	(−2.2983)	(−1.8438)	(−1.7127)	(−1.5971)	(−1.3027)	(−1.2645)

Table 2. *Cont.*

	***FCS*1**			***FCS*2**		
GOV_MKT	−50.9561 **	−55.2345 **	−53.4986 **	−18.7315	−21.3932	−19.1033
	(−2.2530)	(−2.4178)	(−2.3491)	(−0.3577)	(−0.4051)	(−0.3627)
NONSTATE	−100.5866 ***	−95.8197 ***	−102.0321 ***	−211.8248 ***	−209.5521 ***	−214.3893 ***
	(−3.9297)	(−3.6995)	(−3.9693)	(−3.5738)	(−3.4998)	(−3.6066)
Intercept	−3136.5500	−4547.8611	−7306.1470	13,584.5393	11,035.5567	9495.0454
	(−0.6802)	(−0.9918)	(−1.5734)	(1.2722)	(1.0410)	(0.8842)
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
R^2	0.7540	0.7518	0.7518	0.5691	0.5666	0.5664
N	530	530	530	530	530	530

Note: *t* statistics in parentheses. *, **, *** represent $p < 10\%$, $p < 5\%$, $p < 1\%$, respectively. FE is the fixed effect. By plotting the trend of the residuals over time (Figure S1) and conducting the Levin–Lin–Chu test (Table S1), we conclude that *FCS*1, *FCS*2, *CCPA*, *CPU*, and *EPU* exhibit stationarity. Based on the correlation coefficients among all variables (Table S2) and variance inflation factor test (Table S3), there is no obvious collinearity in the regressions.

4.2. Interaction Effect

Based on Equations (7) and (8), the results of the interaction effect regression are in Table 3. The first and third columns report the results based on Equation (7). *CPU* negatively affects *FCS*1 and *FCS*2 at the 1% and 5% significance levels, respectively. The interaction terms between *CCPA* and *CPU* positively affect both *FCS*1 and *FCS*2 at the 1% significance level. For both *FCS*1 and *FCS*2, the positive effect of the interaction terms on *FCS* indicates that *CCPA* can effectively promote China's *FCS* and mitigate the negative impacts of *CPU* on *FCS*. The second and fourth columns present the results based on Equation (8). *EPU* negatively affects *FCS*1 and *FCS*2 at the 1% and 5% significance levels, respectively. The interaction terms between *CCPA* and *EPU* positively affect both *FCS*1 and *FCS*2 at the 5% significance level. In the estimation results of Equation (8), although the coefficient on *CCPA* is negative, it is not significant. For both *FCS*1 and *FCS*2, the interaction terms indicate that the positive impacts of *CCPA* on *FCS* can effectively mitigate the negative impacts of *EPU* on *FCS*; thus, H2 is acceptable.

Table 3. The results of interactive regression.

	***FCS*1**		***FCS*2**	
CCPA	216.1134 *	−50.0872	183.3560	−508.5219
	(1.6615)	(−0.2044)	(0.6073)	(−0.8932)
CPU	−53.6304 ***		−86.5985 **	
	(−3.6558)		(−2.5430)	
CCPA × *CPU*	65.8061 ***		156.5763 ***	
	(4.0213)		(4.1218)	
EPU		−492.1314 ***		−878.1201 **
		(−2.6531)		(−2.0371)
CCPA × *EPU*		589.8263 **		1462.9085 **
		(1.9759)		(2.1089)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
R^2	0.7640	0.7581	0.5846	0.5733
N	530	530	530	530

Note: *t* statistics in parentheses. *, **, *** represent $p < 10\%$, $p < 5\%$, $p < 1\%$, respectively. FE is the fixed effect.

4.3. Channels Analysis

The results for the mediation effects are in Table 4. Paths A, B, C, and D represent the mediation effects of *CCPA* through *TA*, *FA*, *REC*, and *GI* on *FCS*1 and *FCS*2, respectively.

Table 4. The results of intermediate channels.

	Path A: *TA*			Path B: *FA*		
	TA	***FCS*1**	***FCS*2**	***FA***	***FCS*1**	***FCS*2**
CCPA	10.4429 *** (2.9960)	285.6308 ** (2.2937)	341.3122 (1.1733)	45.0258 ** (2.3322)	102.6283 ** (2.2203)	99.1737 (0.4269)
TA		8.9434 *** (5.4557)	17.6141 *** (4.5997)			
FA					6.1386 *** (55.6705)	9.4630 *** (17.0747)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
R^2	0.2103	0.7688	0.5879	0.7420	0.9679	0.7352
	Path C: *REC*			**Path D: *GI***		
	REC	***FCS*1**	***FCS*2**	***GI***	***FCS*1**	***FCS*2**
CCPA	230.7898 *** (3.4645)	212.7006 * (1.7827)	61.9974 (0.2332)	0.1952 *** (4.4323)	233.6507 * (1.8619)	343.2679 (1.1526)
REC		0.7207 *** (8.7970)	2.0073 *** (10.9979)			
GI					744.5966 *** (5.7600)	932.1140 *** (3.0382)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
R^2	0.6126	0.7891	0.6581	0.3554	0.7704	0.5775
N	530	530	530	530	530	530

Note: *t* statistics in parentheses. *, **, *** represent $p < 10\%$, $p < 5\%$, $p < 1\%$, respectively. FE is the fixed effect.

4.3.1. Forest Tending Area

CCPA has a positive impact on *TA* at the 1% significance level, and *TA* has a positive impact on *FCS*1 and *FCS*2 at the 1% significance level. This indicates a significant positive mediation effect of *TA*, suggesting that *CCPA* increases *FCS* by promoting *TA*. Forestry carbon sequestration, as a cost-effective measure for tackling climate change, is receiving more attention and recognition. Forest tending, as an important approach for carbon sequestration in forest management, is also gaining favor among developers of forestry carbon sequestration projects. As a result, *CCPA* promotes the expansion of *TA*.

4.3.2. Forest Area

CCPA has a positive effect on *FA* at the 5% significance level, and *FA* has a positive effect on *FCS*1 and *FCS*2 at the 1% significance level. This indicates a significant positive mediation effect of *FA*, suggesting that *CCPA* promotes the growth of *FCS* by increasing *FA*. One possible explanation is that as the government gives weight to climate change and forestry, the value of forestry carbon sequestration gradually outweighs the value of timber. As a result, rational forest farmers may extend the rotation period of timber harvesting to increase forestry carbon sequestration while reducing timber production [53]. This leads to an annual increase in *FA* and a continuous improvement in China's *FCS*.

4.3.3. Renewable Energy Consumption

CCPA has a positive impact on *REC* at the 1% significance level, and *REC* has a positive impact on *FCS*1 and *FCS*2 at the 1% significance level. This indicates a significant positive mediation effect of *REC*, suggesting that *CCPA* increases *FCS* by increasing *REC*. One possible explanation is that as the government pays more attention to climate change and forestry, there is increased regulation of greenhouse gas emissions, limiting the consumption of fossil fuels, such as coal and oil, while encouraging the consumption of renewable energy sources, such as solar and hydropower. This aligns with the goals outlined in China's "Dual Control System for Energy Consumption and energy intensity". The increase in REC not only reduces carbon dioxide emissions but also promotes an increase in FCS [31].

4.3.4. Green Investment

$CCPA$ has a positive effect on GI at the 1% significance level, and GI has a positive effect on $FCS1$ and $FCS2$ at the 1% significance level. This indicates a significant positive mediation effect of GI, suggesting that $CCPA$ increases FCS by increasing the GI. When taking a lot of note of climate change and forestry, there is increasing government regulation of greenhouse gas emissions from enterprises. Rational enterprises, driven by tightening carbon emission quotas and profit maximization, may enhance research and development of green technologies, such as energy conservation, emission reduction, and carbon sequestration. They may also reduce their own carbon emissions and trade excess carbon quotas in the carbon market. Additionally, companies may offset their carbon emissions through the development of forestry carbon sequestration projects and trade the surplus of China Certified Emission Reductions (CCERs) credits in the carbon market.

Based on the above four results, the claim of H3 is acceptable.

4.4. Robustness

4.4.1. Instrumental Variable Test

When analyzing the impact of $CCPA$ on FCS, there may be endogeneity issues. The $CCPA$ variable generated through frequency analysis of vocabularies could suffer from measurement errors, which may result in an incomplete and imprecise measurement of the government's attention to climate change and forestry. Consequently, this could cause biased estimation results. The results of the Hausman test also indicate the existence of endogeneity (Table S4). $WIND$ is selected as an instrumental variable to tackle the endogeneity problem. On this basis, the causal effects of $CCPA$ on FCS are re-examined using the 2SLS and GMM methods. The results show that whether using the 2SLS or GMM estimation methods, $CCPA$ consistently exhibits a positive impact on FCS, indicating the robustness of the baseline regression (Table S5).

4.4.2. Bootstrap Tests for Intermediate Channels

According to the results in Table 4, the coefficients β_1, β_2, and η in Equations (4), (9) and (10) are all significant, so there is no need to perform the Sobel test. However, following the suggestion of Jiang [52], we conducted a bootstrap mediation analysis to test the robustness of the stepwise regression results for these four pathways. Specifically, with a random seed set to 2023, we estimated the mediation effects of TA, FA, REC, and GI, and provided 95% bias-corrected and accelerated (BCA) confidence intervals. The results are shown in Table S6. The mediation effects of TA, FA, REC, and GI are all significantly positive, consistent with the results obtained through the stepwise regression approach, indicating the robustness of the mediation effect estimates.

5. Heterogeneity Analysis

5.1. Regional Heterogeneity

5.1.1. Heterogeneity in Different Regions

Under different levels of economic development, talent foundation, and technological research and development, $CCPA$ may play different roles in mitigating and adapting to climate change. Therefore, based on the level of economic expansion, we divide the 30 provinces of mainland China into two subsamples: the east and middle regions, and the west region (The east and middle regions include 21 provinces and municipalities: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Heilongjiang, Jilin, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan. The west region includes nine provinces: Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang). We analyze the impact of *CCPA* on *FCS* within each subsample. The results are in Panel A of Table 5. The results of the first and third columns indicate that the effect of *CCPA* on *FCS* is not significant in the east and middle regions. One possible explanation is that the economic expansion level in these provinces is relatively high, and they have the capital and talent foundation for the innovation of energy-saving and carbon-reducing technologies. The main impact of *CCPA* may be reflected in reducing greenhouse gas emissions rather than increasing *FCS*. Besides, enterprises in the east and middle regions can select to purchase forest carbon offset credits from the west, where the economic foundation is relatively weak while forest resources are relatively abundant. It allows them to offset their carbon emissions, so *CCPA* does not influence the *FCS* significantly. The results of the second and fourth columns indicate that *CCPA* has a significant positive impact on *FCS* in the west. This result may be due to the relatively weak economic foundation and the abundance of forest resources in the west. Therefore, the influence of *CCPA* is mainly reflected in the growth of *FCS*. Enterprises can develop forestry carbon sequestration projects to offset their carbon emissions. Meanwhile, they can sell the surplus forestry carbon credits in the carbon market to generate profits, thereby promoting the growth of *FCS*.

Table 5. Regional heterogeneity.

	Panel A: Heterogeneity in Different Regions				**Panel B: Heterogeneity of Artificial and Natural Forests**			
	***FCS*1**		***FCS*2**		***FCS*1**		***FCS*2**	
	East & Middle	**West**	**East & Middle**	**West**	**Artificial**	**Natural**	**Artificial**	**Natural**
CCPA	170.5180	241.3429 **	−4.5132	959.5770 **	82.0113	746.8965 **	135.8979	2378.1117 ***
	(1.0167)	(1.9880)	(−0.0138)	(2.2129)	(1.0331)	(2.4811)	(0.7568)	(2.6631)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.6841	0.9687	0.4916	0.9010	0.9734	0.9602	0.8768	0.9205
N	378	162	378	162	157	108	157	108

Note: *t* statistics in parentheses. *, **, *** represent $p < 10\%$, $p < 5\%$, $p < 1\%$, respectively. FE is the fixed effect.

5.1.2. Heterogeneity of Artificial and Natural Forests

Different logging policies can lead to varying rates of *FCS* growth and result in different effects of *CCPA* on *FCS* (In 2015, the State Council issued the "Reform Plan for State-Owned Forest Farms" and the "Guiding Opinions on Reforming State-Owned Forest Areas", which explicitly stated that by 2020, the commercial logging of natural forests would be gradually halted and the commercial logging of artificial forests would be reduced by approximately 20%). Among the three major forest regions in China, the southern collective forest region consists of artificial forests, while the southwest forest region and northeast forest region consist of natural forests. Therefore, the Chinese forest regions are divided into the artificial forest region and the natural forest region (The artificial forest region includes ten provinces: Zhejiang, Anhui, Jiangxi, Fujian, Hubei, Hunan, Guangdong, Guangxi, Hainan, and Guizhou. The natural forest region includes six provinces: Sichuan, Yunnan, Heilongjiang, Jilin, Liaoning, and Inner Mongolia) for the sample test of the impact of *CCPA* on *FCS*, as shown in Panel B of Table 5. The results of the fifth and seventh columns indicate that the impact of *CCPA* on *FCS* is not significant in the artificial forest region. And the results of the sixth and eighth columns show that *CCPA* has a beneficial impact on *FCS*1 and *FCS*2 in the natural forest region at the significance levels of 5% and 1%, respectively. One possible reason is that the Chinese government has implemented the Natural Forest Protection Project, which imposes strict restrictions on the harvest of natural forests. As the effectiveness of natural forest protection gradually becomes more apparent, the *FCS* of natural forests continues to accumulate. In contrast, commercial felling in artificial forests is subject to fewer restrictions, resulting in slower growth of *FCS*. Therefore, the impact of *CCPA* on *FCS* growth in artificial forests is not significant.

5.2. Heterogeneity Based on Pollutant Discharge Permit Enterprises

Different levels of carbon emission regulations can affect the carbon emission quotas of emission control enterprises, thereby exhibiting heterogeneity in the growth of FCS. Generally, regions with higher levels of carbon emission regulations have lower carbon emission quotas for emission control enterprises. At the same time, enterprises can enhance their corporate social responsibility (CSR) by actively reducing emissions and purchasing forestry carbon sinks, ultimately promoting the growth of FCS. Therefore, the carbon emission regulation levels are represented by the number of pollutant discharge permit enterprises in each province. The results are listed in Table 6.

Table 6. Heterogeneity based on pollutant discharge permit enterprises.

	Threshold		***FCS*1**		**Threshold**		***FCS*2**	
Interval_1	2460	−219.0337 (−1.2093)	26.5269 (0.1496)	23.5122 (0.1340)	935	−1245.9907 ** (−2.2303)	−272.7037 (−0.5865)	−287.3472 (−0.6233)
Interval_2	2624	454.9438 *** (3.6335)	930.7401 *** (6.4304)	918.5297 *** (6.4090)	2112	627.9173 ** (2.1795)	1322.5233 *** (3.9412)	1301.1445 *** (3.9095)
Interval_3	3588		307.9593 ** (2.5010)	300.1907 ** (2.4625)	3640		443.6983 (1.5197)	427.1014 (1.4750)
Interval_4	50,336			840.9109 *** (4.1435)	50,336			1602.3818 *** (3.3287)
F statistics		243.6300 ***	225.3900 ***	224.5000 ***		724.3200 **	687.7500 ***	691.0500 ***

Note: t statistics in parentheses. *, **, *** represent $p < 10\%$, $p < 5\%$, $p < 1\%$, respectively.

The first and fifth columns of Table 6 represent the threshold values for the impact of $CCPA$ on $FCS1$ and $FCS2$, respectively. The second to fourth columns and the sixth to eighth columns represent the estimated coefficients of $CCPA$ on $FCS1$ and $FCS2$ when there is a single threshold, dual thresholds, and three thresholds, respectively. Taking the three-threshold effect as an example, as the number of pollutant discharge permit enterprises increases, the impact of $CCPA$ on FCS shows a U-shaped relationship, initially decreasing and then increasing. One possible reason is that when there are relatively few pollutant discharge permit enterprises, the demand for CCERs, including FCS, from emission control enterprises weakens as the number of pollutant discharge permit enterprises grows. It leads to a decrease in the impact of $CCPA$ on FCS. However, when the number of pollutant discharge permit enterprises exceeds a certain threshold, the government strengthens the regulation of carbon emission quotas to achieve low-carbon transformation and development goals. This increases the demand for FCS from enterprises that control emissions, ultimately resulting in a continuous strengthening of the effect of $CCPA$ on FCS.

6. Discussion

Compared to current literature that focuses solely on studying the impact of $CCPA$ on FCS in the context of forestry ecological engineering or forestry policies, this article generates a composite index reflecting the government's attention to climate change and forestry based on Government Work Reports and Five-Year Plans. Using this index in the regression, the results can provide a more comprehensive reflection of the government's influence on FCS in comparison to existing studies. Another highlight of this article is that to ensure scientific and rational results, we adopt the methods or the data of two authoritative teams in China for measuring FCS. Specifically, the $FCS1$ is estimated using the biomass density calculation method developed by the team of Academician Fang Jingyun [37], while the $FCS2$, calculated through multisource remote sensing monitoring and data fusion, is directly used by the team led by Academician Fu Bojie [38,39]. Comparing the results obtained from regressing different sources of FCS on relevant variables can ensure the robustness of the conclusions to some extent.

In addition, the existing literature predominantly evaluates the impact of CPU or EPU on the ecological environment using indicators such as carbon emissions or ecological footprint, with less emphasis on forest carbon stocks as a measure of the ecological environment. In this article, when regressing *FCS* on *CCPA*, *EPU*, or *CPU* separately, similar conclusions to previous studies are obtained, that is, *CCPA* promotes *FCS* growth [7,8], while *EPU* or *CPU* has adverse effects on the ecological environment [12–22]. However, different from the existing literature, this article compares the positive impact of *CCPA* on *FCS* with the negative impact of *EPU* or *CPU* on *FCS* by incorporating the interaction terms of *CCPA* with *EPU* or *CPU* into the regression. The results indicate that *CCPA* mitigates the negative impact of *EPU* or *CPU* on *FCS*. Furthermore, this article provides further analysis of the underlying mechanisms and heterogeneity of the influence of *CCPA* on *FCS*.

The results of this article are expected to provide valuable theoretical references for legislative departments, economic decision-making departments, and ecological and forestry departments in various fields and sectors. These findings can contribute to the formulation of laws and regulations and the improvement of policy systems, such that China can properly respond to the challenges brought by climate change and achieve the carbon peak and carbon neutrality targets as scheduled. It will also ensure high-quality economic and social development and promote harmonious coexistence between humans and nature.

It should be noted that this article has the following limitations: (1) The measurement accuracy of *CCPA* could be further improved. This article primarily uses government work reports to synthesize *CCPA*. In future research, the material sources can be further expanded to authoritative newspaper articles in China. This expansion entails a considerable amount of work but can effectively improve the performance of *CCPA*. (2) This article uses data from multiple sources for empirical research, and the acquisition of some data is limited. Once relevant data are released and updated, a more objective evaluation can be made.

7. Conclusions and Implications

7.1. Conclusions

This article introduces the *CCPA* index, which reflects the Chinese government's attention to climate change and forestry, and the adjusted *CPU* and *EPU* to examine their impact on China's *FCS*. On this basis, we use a two-way fixed effects model using panel data from 30 provinces in China from 2000 to 2017 to analyze the impacts of *CCPA*, *CPU*, and *EPU* on *FCS*. In addition, this article includes the interaction terms in the baseline regression to assess the impacts of *CCPA* with *CPU* or *EPU* on *FCS*. Furthermore, the article employs a stepwise regression method to test the mediating pathways about *TA*, *FA*, *REC*, and *GI*, which can explain the channels through which *CCPA* affects *FCS* growth. Finally, a heterogeneity analysis is conducted under different conditions. The results show that (1) *CCPA* can significantly promote the growth of *FCS*, while *CPU* or *EPU* would inhibit the growth of *FCS*. (2) The positive effect of *CCPA* on *FCS* growth can mitigate the inhibiting impact of *CPU* or *EPU* on *FCS* growth. (3) *CCPA* can promote *FCS* growth by increasing *TA*, *FA*, *REC*, and *GI*; that is, *TA*, *FA*, *REC*, and *GI* show positive indirect effects, which can also be tested by mediation analysis. Furthermore, the results of bootstrap tests indicate that the indirect effects of all intermediate variables are also positive, indicating the robustness of the conclusions. (4) The heterogeneity analysis shows significant differences in the effect of *CCPA* on *FCS*. In terms of the heterogeneity in regions, the effect of *CCPA* on *FCS* is not significant in the east and middle regions but is significantly positive in the west region. Regarding the heterogeneity in forest regions, the effect of *CCPA* on *FCS* is not significant in the artificial forest region but is significantly positive in the natural forest region. Regarding the heterogeneity in the numbers of pollutant discharge permit enterprises, the effect of *CCPA* on *FCS* exhibits a U-shaped relationship, initially decreasing and then increasing as the number of pollutant discharge permit enterprises increases.

7.2. Implications

Based on the above conclusions, the following three implications can be drawn to promote the growth of FCS in China:

(1) The Chinese government should continue to prioritize climate change, environmental protection, and low-carbon economic transformation. Two aspects should be considered. First, improve related laws and regulations on forest resource protection and ecological restoration. In addition, improve the methodology of forestry carbon sequestration projects, expedite the restart of CCER, and innovate forest carbon trading mechanisms to contribute to the forestry sector's efforts toward achieving the carbon peak and carbon neutrality targets. Second, strive to maintain the continuity of domestic climate and economic policies to avoid adverse impacts of policy uncertainty on economic activities and FCS.

(2) The Chinese government should formulate and implement more environmental- and energy-related policies to practice $CCPA$ and further promote the growth of FCS in China. First, it should improve the management of forest resources, impose reasonable restrictions on forest harvesting, achieve stable growth in forest areas, and continuously improve forest quality, thereby ensuring a steady increase in FCS. Second, it should limit the consumption of non-renewable energy sources, such as fossil fuels, encourage the consumption of renewable energy sources, such as woody biomass, and strengthen the research, promotion, and application of green technologies.

(3) The implementation of climate policies should be tailored to local conditions, with different climate policies being implemented according to regional characteristics and management features. First, for the east and middle region in China, climate policies should concentrate on achieving direct reductions in greenhouse gas emissions. While for the west region, climate policies should aim to fully exploit the imperative role of FCS. Second, efforts should continue to be made in natural forest conservation. Commercial logging of artificial forests should be reasonably restricted, and forests should be rationally managed, e.g., by extending rotation of certain tree species and requiring higher basal areas after thinning harvests. The carbon sequestration potential of the collective forest region in the south should be fully exploited. Finally, it is important to limit the total greenhouse gas emissions of enterprises and to strengthen the regulation of carbon emission quotas as the number of pollutant discharge permit enterprises increases.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f14112273/s1, Equations (S1)–(S3): The specific calculation process of $FCS1$, see references [37,54]; Equation (S4): The specific calculation process of $FCS2$; Equations (S5) and (S6): The procedure for Hausman test; Figure S1: The trend of the residuals over time; Table S1: The results of the stationarity test for the main variables; Table S2: The correlation coefficients among all variables; Table S3: The mean VIF in different regression equations, see reference [55]; Table S4: The results of Hausman test; Table S5: The results of instrumental variable test; Table S6: The results of bootstrap tests.

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Abbreviations

AGBC	aboveground biomass carbon stocks	*AGRI*	agricultural value added
BGBC	belowground biomass carbon stocks	CCER	China certified emission reductions
CCPA	climate change policy attention	*COVER*	forest coverage rate
CPU	climate policy uncertainty	*FA*	forest area
FCS	forest carbon stocks	*GDPG*	GDP growth rate
GDPP	logarithm of per capita GDP	*GI*	green investment
GOV_MKT	the relationship between government and market	*IMEX*	total import and export value
INDU	industrial value added	*INVEST*	the logarithm of forestry investment
NONSTATE	the development of the non-state sector	*OPEN*	openness
PEST	forest pest control area	*POPG*	population growth rate
REC	renewable energy consumption	*SERV*	service industry value added
STRUC	energy structure	*TA*	forest tending area
URBA	urbanization rate	*WIND*	average wind speed

Notes: Abbreviations of variables are indicated in italics. Abbreviations in the list are arranged in alphabetical order based on their first letters.

References

1. Richards, K.R.; Moulton, R.J.; Birdsey, R.A. Costs of creating carbon sinks in the U.S. *Energy. Convers. Manag.* **1993**, *34*, 905–912. [CrossRef]
2. Xu, J.; Yi, Y. Nature—Based Solutions in Meeting China's Dual—Carbon Goal: The Potential of Forest and Policy Needs. *Issues Agric. Econ.* **2022**, *513*, 11–23. (In Chinese) [CrossRef]
3. Lin, B.; Ge, J. How does institutional freedom affect global forest carbon sinks? The analysis of transfer paths. *Resour. Conserv. Recy.* **2020**, *161*, 104982. [CrossRef]
4. Lin, B.; Ge, J. Does institutional freedom matter for global forest carbon sinks in the face of economic development disparity. *China Econ. Rev.* **2021**, *65*, 101563. [CrossRef]
5. Ge, J.; Lin, B. Does the Kyoto Protocol as an International Environmental Policy Promote Forest Carbon Sinks. *J. Glob. Inf. Manag.* **2021**, *30*, 1–22. [CrossRef]
6. Zhao, N.; Wang, K.; Yuan, Y. Toward the carbon neutrality: Forest carbon sinks and its spatial spillover effect in China. *Ecol. Econ.* **2023**, *209*, 107837. [CrossRef]
7. Yuan, N.; Wang, E.; Lv, S.; Tang, X.; Wang, T.; Wang, G.; Zhou, Y.; Zhou, G.; Shi, Y.; Xu, L. Degradation reduces greenhouse. gas emissions while weakening ecosystem carbon sequestration of Moso bamboo forests. *Sci. Total Environ.* **2023**, *877*, 162915. [CrossRef]
8. Daigneault, A.; Baker, J.S.; Guo, J.; Lauri, P.; Favero, A.; Forsell, N.; Johnston, C.; Ohrel, S.B.; Sohngen, B. How the future of the global forest sink depends on timber demand, forest management, and carbon policies. *Glob. Environ. Chang.* **2022**, *76*, 102582. [CrossRef]
9. Liu, W.; Lin, C.; Su, K. Modelling the spatial forest-thinning planning problem considering carbon sequestration and emissions. *For. Policy Econ.* **2017**, *78*, 51–66. [CrossRef]
10. Xu, X.; Liu, J.; Jiao, F.; Zhang, K.; Ye, X.; Gong, H.; Lin, N.; Zou, C. Ecological engineering induced carbon sinks shifting from decreasing to increasing during 1981–2019 in China. *Sci. Total Environ.* **2023**, *864*, 161037. [CrossRef]
11. Zhai, J.; Ling, W.; Liu, Y.; Wang, C.; Mao, X. Assessing the effects of China's Three-North Shelter Forest Program over 40 years. *Sci. Total Environ.* **2023**, *857*, 159354. [CrossRef] [PubMed]
12. Gavriilidis, K. Measuring Climate Policy Uncertainty. 2021. Available online: https://ssrn.com/abstract=3847388 (accessed on 15 November 2023).
13. Guo, J.; Long, S.; Luo, W. Nonlinear effects of climate policy uncertainty and financial speculation on the global prices of oil and gas. *Int. Rev. Financ. Anal.* **2022**, *83*, 102286. [CrossRef]
14. Shang, Y.; Han, D.; Gozgor, G.; Mahalik, M.M.; Sahoo, B.K. The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States. *Renew. Energy* **2022**, *197*, 654–667. [CrossRef]
15. Li, Z.; Su, C.; Moldovan, N.; Umar, M. Energy consumption within policy uncertainty: Considering the climate and economic. factors. *Renew. Energy* **2023**, *208*, 567–576. [CrossRef]
16. Lin, B.; Zhao, H. Tracking policy uncertainty under climate change. *Resour. Policy* **2023**, *83*, 103699. [CrossRef]

17. Zeng, Q.; Ma, F.; Lu, X.; Xu, W. Policy uncertainty and carbon neutrality: Evidence from China. *Financ. Res. Lett.* **2022**, *47*, 102771. [CrossRef]
18. Guesmi, K.; Makrychoriti, P.; Spyrou, S. The relationship between climate risk, climate policy uncertainty, and CO_2 emissions: Empirical evidence from the US. *J. Econ. Behav. Organ.* **2023**, *212*, 610–628. [CrossRef]
19. Xu, P.; Hussain, M.; Ye, C.; Wang, J.; Wang, C.; Geng, J.; Liu, Y.; Chen, J. Natural resources, economic policies, energy structure, and ecological footprints' nexus in emerging seven countries. *Resour. Policy* **2022**, *77*, 102747. [CrossRef]
20. Hussain, M.; Arshad, Z.; Bashir, A. Do economic policy uncertainty and environment-related technologies help in limiting. ecological footprint? *Environ. Sci. Pollut. Res.* **2022**, *29*, 46612–46619. [CrossRef]
21. Zhou, X.; Jia, M.; Altuntas, M.; Kirikkaleli, D.; Hussain, M. Transition to renewable energy and environmental technologies: The. role of economic policy uncertainty in top five polluted economies. *J. Environ. Manag.* **2022**, *313*, 115019. [CrossRef]
22. Yu, J.; Shi, X.; Guo, D.; Yang, L. Economic policy uncertainty (EPU) and firm carbon emissions: Evidence using a China provincial EPU index. *Energy Econ.* **2021**, *94*, 105071. [CrossRef]
23. Zhang, Q.; Cheng, B.; Diao, G.; Tao, C.; Wang, C. Does China's natural forest logging ban affect the stability of the timber import. trade network? *For. Policy Econ.* **2023**, *152*, 102974. [CrossRef]
24. Zinda, J.A.; Trac, C.J.; Zhai, D.; Harrell, S. Dual-function forests in the returning farmland to forest program and the flexibility. of environmental policy in China. *Geoforum* **2017**, *78*, 119–132. [CrossRef]
25. Lin, B.; Ge, J. To harvest or not to harvest? Forest management as a trade-off between bioenergy production and carbon sink. *J. Clean. Prod.* **2020**, *268*, 122219. [CrossRef]
26. Li, W.; Chen, J.; Zhang, Z. Forest quality-based assessment of the Returning Farmland to Forest Program at the community level in SW China. *For. Ecol. Manag.* **2020**, *461*, 117938. [CrossRef]
27. Liu, Y.; Yang, L.; Zhang, J.; Zhang, J.; Li, X.; Zhu, N.; Zhou, M. Evolution and assessment of forest carbon sink policy over the past 20 years. *Acta Ecol. Sin.* **2023**, *43*, 3430–3441. (In Chinese) [CrossRef]
28. Tian, H.; Zhu, J.; Jian, Z.; Ou, Q.; He, X.; Chen, X.; Li, C.; Li, Q.; Liu, H.; Huang, G.; et al. The Carbon Neutral Potential of Forests. in the Yangtze River Economic Belt of China. *Forests* **2022**, *13*, 721. [CrossRef]
29. Li, B.; Gao, G.; Luo, Y.; Xu, M.; Liu, G.; Fu, B. Carbon stock and sequestration of planted and natural forests along climate gradient in water-limited area: A synthesis in the China's Loess plateau. *Agric. For. Meteorol.* **2023**, *333*, 109419. [CrossRef]
30. Shah, W.U.H.; Hao, G.; Yan, H.; Zhu, N.; Yasmeen, R.; Dinca, G. Role of renewable, non-renewable energy consumption and carbon emission in energy efficiency and productivity change: Evidence from G20 economies. *Geosci. Front.* **2023**, 101631, *in press*. [CrossRef]
31. Kwakwa, P.A. Climate change mitigation role of renewable energy consumption: Does institutional quality matter in the case. of reducing Africa's carbon dioxide emissions? *J. Environ. Manag.* **2023**, *342*, 118234. [CrossRef]
32. Yang, Z.; Zhang, M.; Liu, L.; Zhou, D. Can renewable energy investment reduce carbon dioxide emissions? Evidence from scale. and structure. *Energy Econ.* **2022**, *112*, 106181. [CrossRef]
33. Li, K.; Kirkland, S.; Yeo, B.L.; Tubbesing, C.; Bandaru, V.; Song, L.; Holstege, L.; Hartsough, B.; Kendall, A.; Jenkins, B. Integrated economic and environmental modeling of forest biomass for renewable energy in California: Part I—Model development. *Biomass Bioenergy* **2023**, *173*, 106774. [CrossRef]
34. Jin, C.; Lv, Z.; Li, Z.; Sun, K. Green finance, renewable energy and carbon neutrality in OECD countries. *Renew. Energy* **2023**, *211*, 279–284. [CrossRef]
35. Gong, Q.; Ying, L.; Dai, J. Green finance and energy natural resources nexus with economic performance: A novel evidence. from China. *Resour. Policy* **2023**, *84*, 103765. [CrossRef]
36. Shi, D.; Chen, L.; Wang, X.; Xu, X.; Yang, L. Rural venture investments with credits mortgaged on farmer's forests—A case study of Zhejiang, China. *For. Policy Econ.* **2022**, *143*, 102814. [CrossRef]
37. Xu, B.; Guo, Z.; Piao, S.; Fang, J. Biomass carbon stocks in China's forests between 2000 and 2050: A prediction based on forest. biomass-age relationships. *Sci. China Life Sci.* **2010**, *53*, 587–594. [CrossRef]
38. Chen, Y.; Feng, X.; Fu, B.; Ma, H.; Zohner, C.M.; Crowther, T.W.; Huang, Y.; Wu, X.; Wei, F. Above- and belowground forest biomass carbon pool in China during 2002~2021. *Natl. Tibet. Plateau Data Cent.* **2023**, *15*, 897–910. [CrossRef]
39. Chen, Y.; Feng, X.; Fu, B.; Ma, H.; Zohner, C.M.; Crowther, T.W.; Huang, Y.; Wu, X.; Wei, F. Maps with 1 km resolution reveal increases in above-and belowground forest biomass carbon pools in China over the past 20 years. *Earth Syst. Sci. Data* **2023**, *15*, 897–910. [CrossRef]
40. Baker, S.R.; Bloom, N.; Davis, S.J. Measuring economic policy uncertainty. *Q. J. Econ.* **2016**, *131*, 1593–1636. [CrossRef]
41. Yin, L.; Wu, C. Environmental regulation and the ecological efficiency of pollution-intensive industries in the Yangtze river. economic belt. *China Soft Sci.* **2021**, *368*, 181–192. (In Chinese) [CrossRef]
42. Ren, X.; Zhang, X.; Yan, C.; Gozgor, G. Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Econ.* **2022**, *113*, 106209. [CrossRef]
43. Bai, D.; Du, L.; Xu, Y.; Abbas, S. Climate policy uncertainty and corporate green innovation: Evidence from Chinese A-share listed industrial corporations. *Energy Econ.* **2023**, *127*, 107020. [CrossRef]
44. Yao, X.; He, W.; Li, J.; Le, W. Climate policy uncertainty through production networks: Evidence from the stock market. *Econ. Lett.* **2023**, *233*, 111405. [CrossRef]

45. Destek, M.; Aslan, A. Renewable and non-renewable energy consumption and economic growth in emerging economies: Evidence from bootstrap panel causality. *Renew. Energy* **2017**, *111*, 757–763. [CrossRef]
46. Wang, J.; Zhang, S.; Zhang, Q. The relationship of renewable energy consumption to financial development and economic. growth in China. *Renew. Energy* **2021**, *170*, 897–904. [CrossRef]
47. Fan, G.; Wang, X.; Zhang, L.; Zhu, H. Marketization Index for China's Provinces. *Econ. Res. J.* **2003**, *3*, 9–18, 89. Available online: https://d.wanfangdata.com.cn/periodical/jjyj200303002 (accessed on 15 November 2023). (In Chinese)
48. Lin, B.; Ge, J. Valued forest carbon sinks: How much emissions abatement costs could be reduced in China. *J. Clean. Prod.* **2019**, *224*, 455–464. [CrossRef]
49. Chen, H. Research on the Spatial Effect of Green Finance Development on Industrial Structure Adjustment. Master's Thesis, China University of Mining and Technology, Xuzhou, China, 2020. (In Chinese) [CrossRef]
50. Dong, Z.; Wang, H. Local-Neighborhood Effect of Green Technology of Environmental Regulation. *Chin. Ind. Econ.* **2019**, *370*, 110–118. (In Chinese)
51. Giesselmann, M.; Schmidt-Catran, A. Interactions in Fixed Effects Regression Models. *Sociol. Method Res.* **2022**, *51*, 1100–1127. [CrossRef]
52. Jiang, T. Mediating Effects and Moderating Effects in Causal Inference. *Chin. Ind. Econ.* **2022**, *410*, 100–120. (In Chinese) [CrossRef]
53. Zhu, T.; Zhao, Q.; Yang, H.; Ding, S. Influence of carbon sink value on China's wood price based on VAR model. *J. Nanjing For. Univ. Nat. Sci. Ed.* **2018**, *42*, 191–195. (In Chinese) [CrossRef]
54. Li, S. Research on Economic Problem of Forestry Carbon Sink. Ph.D. Thesis, Northeast Forestry University, Harbin, China, 2005. Available online: https://d.wanfangdata.com.cn/thesis/Y805270 (accessed on 15 November 2023). (In Chinese)
55. Pang, J.; Jin, S.; Zhu, P. The impact of external network relationship on green technological innovation: Promotion or inhibition. *Sci. Technol. Prog. Policy* **2019**, *36*, 1–10. (In Chinese) [CrossRef]