Supplementary Materials

Part S1. Measurement of Forest Carbon Stocks

There are two ways to measure Forest Carbon Stocks.

(1) Forest Carbon Stocks Based on Forest Biomass-Age Relationships. Equation (S1) - (S3):

$$FCS1 = (FCS_{it}^{existing\ forest} + FCS_{it}^{afforestation}) \times \frac{100}{51} \quad \text{(S1)}$$

$$FCS_{it}^{existing\ forest} = \frac{existing\ forest\ area_{it} \times density_{it}^{existing\ forest}}{100} \times \frac{44}{12} \times 0.875 \quad \text{(S2)}$$

$$FCS_{it}^{afforestation} = \frac{afforestation\ area_{it} \times density_{it}^{afforestation}}{100} \times \frac{44}{12} \times 0.875 \quad \text{(S3)}$$

where subscripts i and t represent the province and year, respectively. $FCS1$ is the carbon stocks measured in million tons of CO2 equivalent (tCO2e). $FCS_{it}^{existing\ forest}$ and $FCS_{it}^{afforestation}$ represent the carbon stocks of existing forests and newly planted forests, respectively. $existing\ forest\ area$ and $afforestation\ area$ represent the area of existing forests and newly planted forests, respectively. $density_{it}^{existing\ forest}$ and $density_{it}^{afforestation}$ represent the carbon density of existing forests and newly planted forests, respectively. According to Li (2005), the conversion coefficient between aboveground biomass carbon stocks and total carbon stocks (including aboveground biomass carbon stocks, belowground biomass carbon stocks, and soil carbon stocks) is $\frac{100}{51}$. The conversion coefficient between C and CO2 is $\frac{44}{12}$. The proportion of stand area in the total forest area in the year 2000 is 0.875, assuming no change (Xu et al., 2010). It should be noted that the forest area is derived from the data of the Chinese Forest Resources Inventory, which is carried out every 5 years. Therefore, the data on forest area is supplemented between two consecutive inventory years based on the average annual growth rate. According to the research results of Xu et al. (2010), the parameters for existing forest carbon density and newly planted forest carbon density are also supplemented based on the average annual growth rate.

(2) Forest Carbon Stocks by Estimating Remote Sensing Observations. Equation (S4):

$$FCS2 = forest\ area_{it} \times \frac{density_{AGBC} + density_{BGBC}}{100} \quad \text{(S4)}$$

$FCS2$ represents the forest carbon stocks, which is the sum of AGBC and BGBC, measured in million tons of carbon (MtC). The $forest\ area$ is measured in tens of thousands of hectares (10,000 ha). $density_{AGBC}$ and $density_{BGBC}$ represent the carbon density of aboveground biomass and belowground biomass, respectively, measured in tons of carbon per hectare (tC/ha).

Part S2 Stationarity Test

Part S2.1 The Trend of the Residuals over Time

Figure S1 plots the trend of the residuals over time. There is no significant trend in residuals' variation over time.

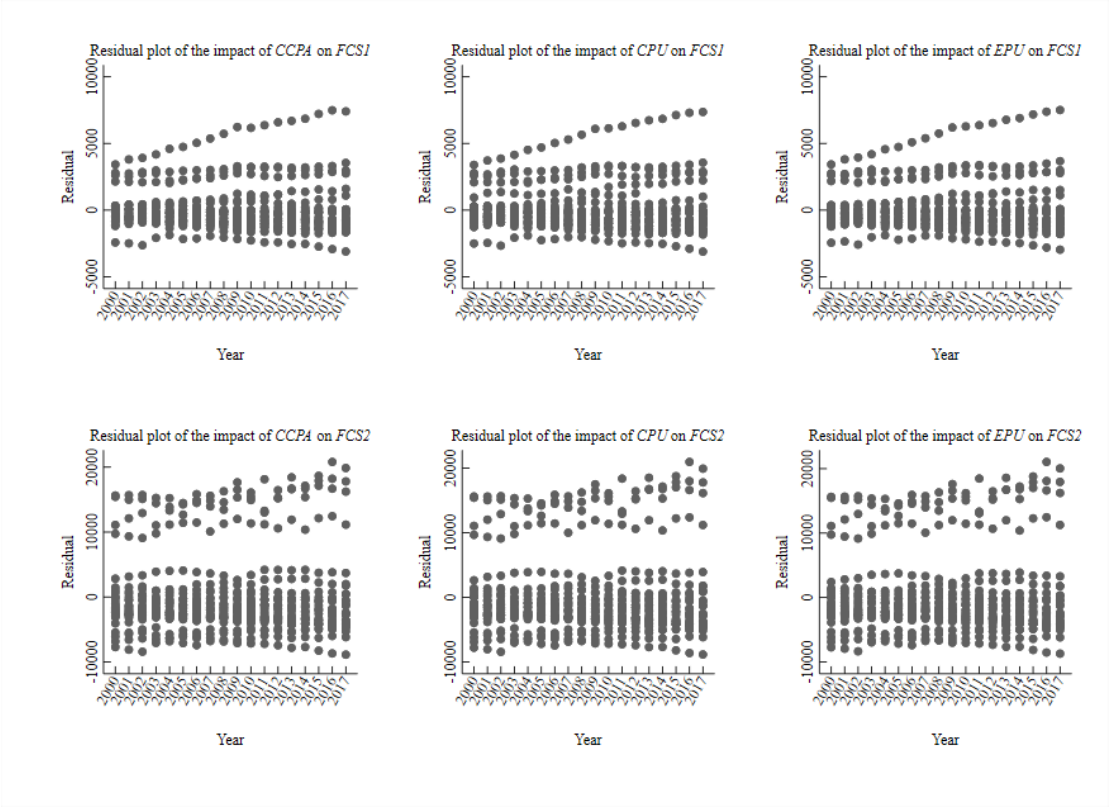

Figure S1. The trend of the residuals over time.

Part S2.2 Levin-Lin-Chu Test

To avoid the problem of spurious regressions caused by non-stationary data, we conducted a stationarity test on the panel data formed by the explanatory variables and the key explanatory variables. Table S1 reports the results of the Levin-Lin-Chu unit root test. All variables rejected the null hypothesis of having a unit root at a significance level of at least 5%, indicating the stationarity of the data.

Table S1 The results of the stationarity test for the main variables.

variables	$FCS1$	$FCS2$	$CCPA$	CPU	EPU
adjusted t* statistic	-5.9658	-8.2588	-4.3332	-1.7730	-6.7349
p-value	0.0000	0.0000	0.0000	0.0381	0.0000

Part S3. The Results of Correlation Coefficients Test and VIF Test

Part S3.1. The Results of Correlation Coefficients Test

Table S2 The correlation coefficients among all variables

	CCPA	*CPU*	*EPU*	*GDPP*	*AGRI*	*INDU*	*SERV*	*URBA*	*GDPG*	*POPG*	*COVERG*	*OPEN*	*STRUC*	*TRADE*	*PEST*	*INVEST*	*GOV_MKT*	*NONSTATE*
CCPA	1.000																	
CPU	-0.016	1.000																
EPU	0.155	-0.037	1.000															
GDPP	0.494	0.406	0.151	1.000														
AGRI	0.272	0.238	0.135	0.400	1.000													
INDU	0.306	0.627	0.056	0.584	0.791	1.000												
SERV	0.309	0.661	0.013	0.669	0.668	0.926	1.000											
URBA	0.300	0.444	0.072	0.830	0.088	0.396	0.536	1.000										
GDPG	-0.028	-0.030	0.154	-0.157	-0.172	-0.148	-0.216	-0.164	1.000									
POPG	-0.110	-0.034	-0.119	-0.180	-0.125	-0.102	-0.098	-0.204	-0.026	1.000								
COVERG	0.134	0.040	0.076	0.123	0.249	0.174	0.174	-0.002	-0.031	-0.072	1.000							
OPEN	-0.186	0.707	-0.057	0.414	-0.128	0.219	0.278	0.590	0.050	-0.018	-0.096	1.000						
STRUC	0.022	-0.084	-0.051	-0.109	-0.027	-0.074	-0.064	-0.150	-0.048	0.016	0.122	-0.103	1.000					
TRADE	0.178	0.306	-0.097	0.433	0.031	0.261	0.432	0.462	-0.125	-0.041	0.055	0.268	-0.024	1.000				
PEST	0.012	-0.178	0.105	-0.039	0.457	0.142	0.048	-0.202	-0.056	-0.054	-0.048	-0.322	-0.070	-0.175	1.000			
INVEST	0.577	-0.054	0.183	0.531	0.589	0.452	0.469	0.272	-0.189	-0.153	0.131	-0.261	-0.059	0.166	0.347	1.000		
GOVMKT	-0.183	0.447	0.022	0.263	0.187	0.381	0.342	0.277	0.185	-0.074	0.226	0.510	-0.077	0.212	-0.138	-0.106	1.000	
NONSTATE	0.274	0.432	0.152	0.778	0.579	0.664	0.633	0.551	-0.037	-0.173	0.360	0.363	-0.107	0.283	0.040	0.364	0.545	1.000

Part S3.2. The Results of VIF Test

When incorporating the EPU, CPU, EPU and CPU in the regression analysis, respectively, the results show that the mean variance inflation factors (VIF) for all the regression equations were less than 10. Referring to Pang et al. (2019), this result indicates the absence of significant collinearity issues. From the perspective of VIF, it can be also seen that the collinearity is not obvious. The values of mean VIF in different Scenarios are reported in Table S3.

Table S3 The mean VIF in different regression equations

	$FCS1$			$FCS2$		
$CCPA$	YES	YES	YES	YES	YES	YES
EPU	YES		YES	YES		YES
CPU		YES	YES		YES	YES
$Controls$	YES	YES	YES	YES	YES	YES
$Mean\ VIF$	4.87	5.56	5.35	4.87	5.56	5.35

Part S4. The results of Hausman Test and Instrumental Variable Test

Part S4.1 The Results of Hausman Test

To test whether CCPA in equation (4) is exogenous, a Hausman test needs to be conducted, as outlined in equations (S4) and (S5).

$$FCS_{it} = \alpha_1' + \beta_1' CCPA_{it} + \beta_2 WIND_{it} + \gamma_1' Controls + \delta_i' + \mu_t' + \varepsilon_{it}', \quad \text{(S5)}$$

$$FCS_{it} = \alpha_1'' + \beta_1'' CCPA_{it} + \beta_3 RESI_{it} + \gamma_1'' Controls + \delta_i'' + \mu_t'' + \varepsilon_{it}'', \quad \text{(S6)}$$

where superscripts are used to distinguish the coefficients in different equations. The $WIND$ is the instrumental variable (average speed), $RESI$ is the residual obtained from the equation (S5), and a significant β_3 indicates that CCPA is endogenous in the equation (4).

Based on equation (S5) to (S6), the Hausman test results are in Table S4. The first and third columns report the results based on equation (S5). The second and fourth columns report the results based on equation (S6). $RESI1$ and $RESI2$ in Table S4 are the residuals obtained from the equation (S5) when performing regression using $FCS1$ and $FCS2$, respectively. The t statistics of $RESI1$ and $RESI2$ are 163.60 and 168.77, respectively, which indicates that *CCPA* is endogenous and the endogeneity needs to be addressed.

Table S4. The results of Hausman test

	$FCS1$		$FCS2$	
$CCPA$	344.3300***	379.0262***	447.3333	525.2544***
	(2.7170)	(22.7967)	(1.5236)	(14.0669)
$WIND$	1164.8488***		2616.0348***	
	(2.8423)		(2.7552)	
RESI 1		**1.0000*** **		
		(163.6018)		
RESI 2				**1.0000*** **
				(168.7730)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
N	530	530	530	530

R^2	0.9723	0.9995	0.9868	0.9998

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

Part S4.2 The Results of Instrumental Variable Test

The first column of Table S5 presents the results of the first-stage regression, which examines the causal effect of $WIND$ on $CCPA$. Controlling year- and province-fixed effects, $WIND$ has a positive impact on $CCPA$ at the 5% significance level. The second and third columns represent the second-stage 2SLS estimation results, showing that $CCPA$ has a positive effect on $FCS1$ and $FCS2$ at the 5% and 1% significance levels, respectively. Regarding the rationality of the instrumental variable, the first-stage F-statistic value is 27.65, exceeding the empirical threshold of 10, indicating the absence of a weak instrument problem. The second-stage LM test statistic is 4.92, rejecting the null hypothesis that the instrumental variable's insufficient identification at the 5% significance level, thus confirming the appropriateness of selecting $WIND$ as an instrumental variable. The fourth and fifth columns present the results of the second-stage GMM estimation, showing that $CCPA$ has a positive effect on both $FCS1$ and $FCS2$ at the 5% significance level. Overall, whether using the 2SLS or GMM estimation methods, $CCPA$ consistently exhibits a beneficial impact on FCS, indicating the robustness of the baseline regression.

Table S5. The results of instrumental variable test

	First stage	Second stage			
		2SLS		GMM	
	$CCPA$	$FCS1$	$FCS2$	$FCS1$	$FCS2$
$WIND$	0.3115**				
	(2.0891)				
$CCPA$		4083.8505**	8845.6040*	4083.8136**	8844.4197**
		(1.9644)	(1.8737)	(2.3459)	(2.0940)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
R^2	0.7889	0.9203	0.9636	0.9203	0.9636
N	530	530	530	530	530
F Test	27.6500***				
LM Test		4.9170**	4.9170**		

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

Part S5. The Results of Bootstrap Tests for Intermediate Channels

Table S6. The results of bootstrap tests

	Path A: TA		Path B: FA	
	$FCS1$	$FCS2$	$FCS1$	$FCS2$
Indirect effect	101.0546**	194.1385**	343.2017***	524.8885***
	(2.5400)	(2.3700)	(3.0100)	(2.9100)
95% Conf. Interval	(30.7711,195.7192)	(61.6622, 375.5455)	(140.7148, 632.9423)	(218.7007, 1049.3280)
Direct effect	321.0702***	324.9823	78.9231*	-5.7677
	(3.6400)	(1.0400)	(1.6500)	(-0.0200)
95% Conf. Interval	(97.7142, 606.1984)	(246.9492, 1033.8300)	(-13.5946, 175.2736)	(-520.9485, 478.6795)
	Path C: REC		Path D: GI	
	$FCS1$	$FCS2$	$FCS1$	$FCS2$
Indirect effect	148.8005**	373.3607**	127.8695***	181.9865**
	(2.5200)	(2.2900)	(2.7000)	(2.0800)
95% Conf. Interval	(48.3274, 277.6585)	(116.8348, 755.4642)	(63.1103, 252.2662)	(33.3261, 428.3368)
Direct effect	273.3243**	145.7601	294.2553**	343.2679
	(2.3600)	(0.4800)	(2.3700)	(0.9900)
95% Conf. Interval	(80.2960, 547.0557)	(-406.3970, 749.7421)	(75.8732, 577.8439)	(-305.7809, 948.8631)

Note: t statistics in parentheses. *, **, *** represent p<10%, p<5%, p<1%, respectively. The 95% Bias-Corrected and Accelerated confidence intervals are reported.

Reference

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3. Pang, J.; Jin, S.; Zhu, P. The impact of external network relationship on green technological innovation: promotion or inhibition. Science &Technology Progress and Policy. 2019, 36, 1-10. 10.6049/kjjbydc.2018090513. (In Chinese)