Effect of Carbon Emission Reduction driven by China's Transition Finance considering the Factors of Technological Progress

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Abstract. In China's "dual carbon" strategy, carbon emission reduction is very important to the green transformation of economic society. This paper assumes that transition financing indirectly drives carbon emission reduction through technological progress, and there is a spatial spillover effect, and examines the impact of transition financing and technological progress on carbon emission reduction. Based on the provincial panel data from 2012 to 2022, the empirical results show that transition financing significantly inhibits carbon emissions, and technological progress plays a mediating role. Transition financing is positively related to the spatial distribution of carbon emissions. This paper puts forward some suggestions, such as strengthening policy support and promoting regional coordination of carbon emission reduction.

Keywords: transitional finance; technological progress; carbon emission reduction; spatial spillover effect; Malmquist index

1 Introduction

In the new stage of China's high-quality economic development, carbon emission reduction has been promoted to a strategic height. Transition finance, as a key driving force for the decarbonization of high-carbon industries, has made remarkable progress: transition finance instruments not only provide financial support, but also reduce risks through protection mechanisms. However, transition financing faces challenges such as policy gaps and limited product diversity. Existing studies have neglected the role of technological innovation in emission reduction. This paper proposes an analytical framework that integrates technological progress and spatial spillovers, aiming to address regional development disparities, improve theoretical understanding, and guide policy making.

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2 Domestic and Foreign Literature Review

Transition finance was first proposed by the OECD in 2019 to help developing countries make a low-carbon transition, which was defined by the CBI 2020 as a “climate mitigation transition” to enable the upgrading of high-carbon sectors. Since 2021, China has established a dual-track "policy + market" system. Theoretically, studies (Omondi, 2023) [1] use models such as non-radial Malmquist index of regional low-carbon dynamics. Research (Zheng, 2020) [2] emphasizes that technology substitution and policy constraints are key risk drivers. Empirical work (Liao, 2019) [3] uses the SBM model to measure the efficiency of industrial green transformation. In practice, the "Porter effect" (Wang R, 2022) [4] is used to support high-carbon industries through green credit and transformation bonds. The existing literature focuses on theoretical mechanisms and policy effects, ignoring the mediating role of technological progress and spatial spillover effects. Using the spatial Durbin model and the intermediary model, this paper explores the path of transition finance to achieve emission reduction through technology diffusion, aiming to inform policy.

3 Variable setting and model construction

3.1 Variable measurement and specification

This study examines 30 Chinese provincial regions (excluding Xizang, HK, Macao, and Taiwan due to data constraints) over 2012-2022, yielding 330 observations. The study involves 8 key variables, including: explained variable: carbon emissions, which is calculated from carbon sources like raw coal, coke, etc.;[5] core explanatory variables: transitional finance is "environmental pollution control investment as a share of GDP"[6]. The mediating variable: technological progress, is measured using the DEA-Malmquist index method. This method assesses multi - period TFP changes and DMU efficiency considering various factors. The study uses 30 provinces (municipalities) as decision - making units.[7] Control variables: level of economic development, degree of government intervention, population density, degree of opening-up, and level of urbanization.

3.2 Research hypothesis and model construction

Transition finance theoretically reduces carbon emissions through two pathways: Technology-driven mechanism: It funds low-carbon R&D and channels resources to innovation-oriented firms, accelerating technological progress as a key emission reduction driver.[8] Spatial spillover effect: in the process of promoting carbon emission reduction through technological progress, transitional finance will have a radiation impact among regions: [9] H1: Transition finance indirectly reduces carbon emissions via technological progress. H2: Transition finance generates positive spatial spillover effects in regional carbon reduction. The model is constructed as follows:

$$CE_{it} = \rho \sum_{j=1}^{n} W_{ij} CE_{it} + \alpha_1 + \beta_k X_k + \theta_k \sum_{i=1}^{n} W_{ij} X_k + +\mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where, CE_{it}: carbon emissions of region i in year t; ρ:Spatial autoregressive coefficient; W_{ij} Spatial weight matrix (0-1 adjacency/geographical distance); X_k:control variable; $\sum_{j=1}^{n} W_{ij}X_k$: spatial lag term of carbon emissions; TF_{it}: Transition finance; θ_k: coefficients of control variables.[10]

4 Empirical analysis

4.1 Results of the Moran index test

The empirical results are shown in table 1, from 2012-2022, the spatial distribution of transition finance had a significant positive correlation. With the 0-1 neighborhood weight matrix, the spatial agglomeration of transition finance development rose from 2012 - 2017. Under the geographical distance weight matrix, its spatial correlation also increased during this period. Moreover, the Moran index was higher in the 0-1 proximity weight matrix than in the geographical distance one. This shows that the direct geographical connection of adjacent areas benefits information exchange and policy coordination, having a more obvious agglomeration effect on transition finance development.

Table 1. Global Moran Index of transitional finance from 2012 to 2022

year	0-1 adjacent weight matrix		Geographical distance weight matrix	
	Moran's I	P value	Moran's I	P value
2012	0.2059*	0.0505	0.0652**	0.0058
2013	0.2180*	0.0401	0.0715**	0.0034
2014	0.2342*	0.0281	0.0870***	0.0007
2015	0.2836**	0.0093	0.1118***	0.0000
2016	0.3149**	0.0044	0.1224***	0.0000
2017	0.3261**	0.0032	0.1237***	0.0000
2018	0.2582*	0.0169	0.1086***	0.0001
2019	0.2301*	0.0316	0.0943***	0.0004
2020	0.2069*	0.0481	0.0748**	0.0023
2021	0.1538	0.1236	0.0514*	0.0169
2022	0.1602	0.1129	0.0357	0.0516

Source: Self-made by the author.

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively.

4.2 Decomposition of spatial spillover effect of transitional finance on carbon emissions

Table 2 shows SDM decomposition results. For the 0-1 adjacency matrix, a 1% rise in transition finance directly cuts local emissions by 0.034% but indirectly raises adjacent emissions by 0.146%, with a net 0.112% total increase. For the geographical distance matrix, a 1% increase directly raises local emissions by 0.071% and indirectly reduces adjacent emissions by 0.158%, resulting in a net -0.088% total effect. The main differences are: the adjacency matrix overestimates spillover because of its binary spatial definitions, making indirect effects exceed direct reductions. The distance matrix ignores non-geographic links, leading to biased estimates where economically integrated regions have stronger spillover than geographically adjacent ones.

Table 2. Spatial effect decomposition of SDM model under the two spatial weight matrices

	0-1 adjacent weight matrix			Geographical distance weight matrix		
Variables	Direct effect ADI	Indirect effect AII	Total effect ATI	Direct effect ADI	Indirect effect AII	Total effect ATI
TF	-0.034	0.146	0.112	0.071	-0.158	-0.088
lnPGDP	-0.018	-0.01	-0.028	0.007	0.069	0.077
GOV	0.129	-0.837	-0.708	-0.014	-1.75	-1.764
lnPD	0.017	-0.008	0.009	0.009	0.142	0.151
OPEN	-0.174	0.148	-0.026	-0.144	-0.981	-1.125
URBAN	0.05	-1.192	-1.142	-0.264	-1.595	-1.86

Source: Self-made by the author.

4.3 Test results of the mediating effect of transitional finance on carbon emissions

The results of the mediating effect model are shown in table 3, mediation model analysis shows that: Transitional finance and technological progress have a significantly negative impact on carbon emissions. Among the mediating variables, the level of economic development is negatively correlated with carbon emissions, while population density is positively correlated. Interaction term: There is an interaction effect between the lagged term of opening-up level and the urbanization level. Therefore, the hypothesis proposed in this paper has been verified.

Table 3. Spatial spillover effect of technological progress (TP) as a mediating variable

	Variables	CE	TP	CE
X term	TF	-0.036**(-17.843)	0.002**(4.829)	-0.033**(-16.66)
	TP			-0.057*(-1.657)
	lnPGDP	-6.786**(5.713)	0.215(0.913)	-6.389**(-5.763)
	GOV	-0.859**(-6.191)	-0.041(-1.491)	-0.935**(-7.201)
	lnPD	0.737**(19.843)	0.077(1.274)	0.732**(19.728)
	OPEN	0.076(0.231)	-0.014(-0.219)	0.050(0.162)
	URBAN	-0.398**(-7.320)	-0.001(-0.018)	-0.398**(-7.332)
W*X term	W*TF	-0.081*(-2.319)	0.132*(2.322)	-0.088*(-2.521)
	W*TP			-0.074*(-2.453)
	W*lnPGDP	0.241(0.986)	0.104(0.259)	0.235(0.965)
	W*GOV	0.106*(2.423)	-0.033(-0.464)	0.108*(2.472)

W*lnPD	0.227(0.816)	0.022(0.395)	0.268(1.029)
W*OPEN	-0.099**(-3.362)	-0.055(-1.140)	-0.096**(-3.258)
W*URBAN	0.399**(-7.343)	0.002(0.032)	-0.399**(-7.367)

Source: Self-made by the author.

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively.

5 Conclusion

The empirical results show that there is a significant negative relationship between scientific and technological progress and carbon emissions. There is a significant positive correlation between transitional finance and the spatial distribution of carbon emissions, and the agglomeration effect is stronger under the 0-1 adjacency matrix and weaker under the geographical distance matrix. transition financing and other variables have significant spatial spillover effects on carbon emissions, but there are differences in the direct effect, indirect effect and total effect under different weight matrices.

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