Journal of Innovation & Knowledge 11 (2026) 100872

Contents lists available at ScienceDirect

Journal of Innovation & Knowledge

journal homepage: www.elsevier.com/locate/jik

The role of financial innovation and Industry 4.0 in decarbonizing resource-intensive industries through threshold effects

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A R T I C L E I N F O

JEL classification:
Q56
O16
O33
L72
R11
Q52

Keywords:
Science and technology finance
Industry 4.0
Carbon emission
Copper mining
Regional economic development
Environmental governance

A B S T R A C T

This study examines the role of science and technology finance (S&TF) and Industry 4.0 innovations in promoting sustainable transformation in China's copper mining industry, with a focus on reducing carbon emissions. Using panel data from 30 Chinese provinces spanning 2011 to 2020, we apply two-way fixed effects and threshold regression models to examine the nonlinear impacts of S&TF on carbon emissions from copper mining (CECM). Our findings demonstrate that a 1 % increase in S&TF is associated with an approximate 0.142 % reduction in CECM, with the effect becoming more pronounced beyond the identified national threshold value of 0.163. The effect is most pronounced in the economically advanced eastern regions but remains relevant across central and western provinces. Furthermore, the effectiveness of S&TF is moderated by regional Industry 4.0 development, which exhibits a U-shaped influence, while economic development strengthens and environmental regulation weakens the impact of decarbonization over time. These findings highlight the need to align financial innovation, regional technological capacity, and governance mechanisms to advance SDG and ESG objectives in resource-intensive industries. The study offers practical insights for developing resilient, innovation-driven financial and governance frameworks that can effectively reduce industrial carbon emissions.

Introduction

Industry 4.0 represents the interconnection of emerging technologies, such as the Internet of Things, big data, and AI, into conventional manufacturing processes, thereby changing the global manufacturing landscape. The rise of artificial intelligence leads the production sector to no longer stand out only in terms of production gaps, and leaves it with data-centric and smart processes. In parallel, it is envisaged that Industry 4.0 demands an upheaval towards an environmentally sustainable approach targeting green production and manufacturing processes. This is accomplished by reducing air, land, and water contamination throughout the life cycle of products, including the usage stage, and implementing sustainable systems for products and technologies (Huang, 2016). With the advent of the global force known as Industry 4.0, a guiding concept for China's industrial development, the nation finds itself in sync with the moment of the world. Quintessential Technology and Scientific Innovation initiatives determine the Beijing 4.0 phenomenon. Therefore, only through formulating the right strategies that recognize these improvements can China successfully sail through the industrial reforms.

As the global community increasingly emphasizes the integration of sustainability goals into economic development, aligning financial and governance systems with low-carbon and inclusive growth has become a strategic priority (Hou et al., 2022; Xu, 2022). In this context, China's copper mining sector presents a compelling case to explore how science and technology finance (S&TF), combined with Industry 4.0 technologies, can contribute to a green transformation (Lu et al., 2022; Dong et al., 2020). This synergy not only supports carbon emission reductions but also strengthens knowledge-based governance by enhancing resource allocation, innovation efficiency, and regulatory responsiveness (Wang et al., 2022; Sheng et al., 2021). Understanding these interconnections is critical for designing sustainable financial frameworks that respond to ecological degradation while advancing regional industrial upgrading and environmental resilience (Dong et al., 2022; Hu

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https://doi.org/10.1016/j.jik.2025.100872
Received 25 July 2025; Accepted 22 October 2025
Available online 30 October 2025

et al., 2017).

The development of modern Chinese industry, which has occurred relatively recently, is undoubtedly remarkable. However, this rapid economic ascent has been paralleled by significant energy consumption and greenhouse gas emissions, particularly carbon dioxide. Coal still dominates as the primary energy source, accounting for roughly 60 % of China's energy consumption, as per National Bureau of Statistics (Dong et al., 2019)data. The substantial emission of greenhouse gases hastens the pace of global warming. China's adoption of a somewhat crude economic development model has propelled its economic growth, but has also propelled China to become the world's largest emitter of carbon dioxide (Wen & Shao, 2019). To prevent further degradation of the global ecological landscape, the Chinese government pledged at the 75th United Nations General Assembly to pursue carbon peaking by 2030 and attain carbon neutrality by 2060 concerning domestic CO_2 emissions. The pressing challenge is effectively balancing carbon emission reduction with economic development, optimizing economic structure to sustain stable growth while steering towards low-carbon economic development (Zhi & Chen, 2023).

Adapting the energy consumption structure and fostering the expansion of new energy sources represent an unavoidable trajectory for China's journey toward a low-carbon economy. Copper is a pivotal metal in new energy source development (Dong et al., 2022). The advancement of new energy sources and restructuring energy consumption patterns will notably escalate the demand for copper, a fundamental material in their development (Watari et al., 2020). While increased copper recycling can mitigate some supply constraints, it remains insufficient to address them entirely (Valero et al., 2018). However, China's copper resources are characterized by low grades. As copper extraction rises and grade levels decline, energy consumption and carbon emissions from copper mining are poised to escalate. Integrating S&TF into copper mining emerges as a promising strategy to curtail carbon emissions associated with the copper mining process (Dong et al., 2020).

The technology financing that consists of AI, the Internet of Things, cloud computing, and other latest technologies can change the financial institutions and markets by improving the business architecture, service models, and types of products and services (Liu et al., 2021). As a new stream in economic practices, cloud computing makes services client-friendly regarding costs and improves operations within financial institutions and markets. Firstly, science and technology finance (S&TF) is a great tool to stimulate R&D and innovation, as it is an easy source of finance for enterprises which they lack otherwise, and may raise technology innovations too (Pagliacci, 2020). S&TF's action of aggregating and distributing capital along with the advancement of eco-friendly technologies is the driving force behind in reducing the level of CO_2 emission of the economy while also promoting green technology innovation (Lu et al., 2022).

In efforts to reduce carbon emissions from copper mining, S&TF plays a crucial role. For the copper mining industry, S&TF represents a new financial model that supports structural improvement by providing more efficient and accessible financial services (Wang et al., 2022). By streamlining financing, this sector improves mining efficiency and lowers barriers to investment (Alquist et al., 2022). At the same time, S&TF directs resources toward green research and development (R&D). These investments drive technological progress by eliminating highly polluting and energy-intensive practices. They also encourage the adoption of technologies that improve energy efficiency and promote the use of low-carbon materials, thereby cutting emissions across the mining process (Sheng et al., 2021; Lu et al., 2022). Most existing studies focus on the link between S&TF and environmental quality, but little research addresses its specific impact on carbon emissions from copper mining. At the enterprise level, scholars argue that S&TF provides tailored financial services that strengthen firms' innovation capacity, accelerate the exit of energy-intensive sectors, and advance high-tech industries (Xu, 2022). From a broader socio-economic perspective, S&TF enhances collaborative innovation, improves the efficiency of green initiatives, and supports industrial upgrading (Li et al., 2022; Wang et al., 2022; Yu et al., 2022). Sustainable development also increases regional total green factor productivity and reduces carbon emissions (Lu et al., 2023; Xu et al., 2022).

Emerging from the deep integration of finance and technology, S&TF represents a new financial paradigm that leverages rapidly evolving digital and information technologies to transform the traditional economic model (Collins & Urban, 2018). The environmental impact of copper production, particularly in terms of greenhouse gas emissions, is a complex issue.

First, raising the regional level of S&TF can drive technological progress. In regions with structural weaknesses in their financial systems, S&TF helps clarify the link between ecological degradation and low levels of technological innovation (Kapetaniou et al., 2018; Ibrahim & Vo, 2021). By enabling the uptake of green technologies, S&TF directly improves environmental quality in copper mining regions. The industrial restructuring, supported by S&TF, reduces energy consumption and lowers greenhouse gas emissions from mining activities (Gao et al., 2023).

Second, S&TF addresses the funding challenges faced by copper mining firms in adopting energy-saving technologies and improving energy efficiency (Hu et al., 2017). By providing financial support for these initiatives, S&TF promotes higher-quality economic growth, reduces regional carbon emissions, and contributes to building a sustainable ecological environment for the future (Hou et al., 2022).

Theoretical analysis and research hypothesis

Based on the preceding analysis in the introduction, which links S&TF to emission reductions through green R&D, technology upgrading, and efficiency improvements. This paper proposes the first research hypothesis:

H1. The progression in S&TF is one of the factors that causes the source region copper mining emissions to decrease.

Another topic that might be considered is how S&TF influences copper mining emissions through different components, like investment size and government support. It's therefore reasonable that this impact is nonlinear, which exists above a certain level of S&TF on carbon emissions from copper mining.

At first, it successfully bridges the copper mining firms' R&D funding attention void, enabling them to improve their capacity. This way, it distributes innovation risk and funding constraints, thus facilitating a more financially harmonious flow of green technology innovation within these enterprises (Cheng et al., 2023). This promotes emerging production and competitiveness in environmentally friendly products (Deng et al., 2015). Nevertheless, these advantages are noteworthy, albeit there is a persistent gap regarding the inadequate capital in the S&T financial ecosystem at this level. Thus, the output of carbon emission reduction remains slow for copper mining companies, hence limiting the overall significance of the S&TF in reducing carbon emissions (Li et al., 2021).

In the early stages of S&TF development, it helps bridge the research and development funding gaps faced by copper mining enterprises. By dispersing innovation risks and easing financing constraints, S&TF facilitates the smooth implementation of green technology innovation within these firms (Cheng et al., 2023). This process encourages the production of more environmentally friendly products (Deng et al., 2015). Nevertheless, the S&T financial ecosystem remains underdeveloped during this stage due to insufficient investment levels. As a result, its impact on carbon emission reduction in copper mining enterprises is limited, thereby constraining the broader influence of S&TF on emission mitigation (Li et al., 2021). As S&TF investment increases, the economy gradually shifts from a traditional factor-driven model to an innovation-oriented one (Wang et al., 2022). In this context, a higher proportion of copper production linked to green technologies incentivizes mining enterprises to allocate more resources toward developing environmentally friendly technologies. Continuous advancements in green technology improve energy efficiency, reduce energy consumption, and lower the release of carbon dioxide, thereby mitigating energy-related pollution (Ahmad et al., 2022).

Meanwhile, these S&T financial ecosystems empower capital allocation parameters, which help financial resources motivate such modern and ecological copper mining businesses. It, in turn, will result in a transition from conventional, polluted, and energy-consumptive processes of copper ore mining to building a new framework for its green development, which consequently will help guarantee environmentally friendly practices in the industry (Sun et al., 2019).

Having an opportunity for exchange for science, technology, and financial funds, S&TF can help copper mining companies secure and efficiently obtain financial resources, such as new energy-saving technologies and emission reduction. These advancements additionally contribute to regional carbon emission reduction (Zhou & Wang, 2023). This circular effect improves itself by increasing the influence of S&TF on the carbon emission of copper mining.

Building upon the preceding analysis of how S&TF effects may be minor initially due to limited investment but grow stronger as financial inputs increase, indicating a nonlinear relationship, this paper introduces the second research hypothesis:

H2. The influence of S&TF on carbon emissions from the copper mine is considered a non-linear pattern; specifically, the impact of S&TF on reducing carbon emissions increases with higher levels of S&TF investment.

The effectiveness of S&TF in reducing carbon emissions from copper mining depends on several factors, including domestic Industry 4.0 development, economic growth, and environmental policies. Industry 4.0 technologies, such as the Internet of Things and artificial intelligence, increase the technological sophistication of the financial system (Soni et al., 2022). Financial institutions also apply advanced Information and Communication Technologies (ICT) to improve energy efficiency, with evidence showing reduced carbon emissions in regions adopting ICT innovations (Probst et al., 2021; Azam et al. (2021). In the mining industry, Industry 4.0 applications enhance efficiency and environmental performance, thereby reducing costs associated with labor, resource extraction, energy use, and emissions (Zhironkin & Taran, 2023).

Beyond Industry 4.0, broader economic and regulatory conditions also shape the role of S&TF in emission reduction. Since financial progress is closely linked to economic growth, the latter has a significant influence on the effectiveness of S&TF in reducing emissions (He et al., 2019; Osobajo et al., 2020). Environmental policies push copper mining enterprises toward greener practices, which require substantial financial support for technological upgrades (Guo et al., 2020). Yet, overly strict regulations may hinder production if firms consider the cost of green innovation too high (Du et al., 2021). Affordable financial services provided by S&TF can ease this burden, enabling green transitions, lowering carbon footprints, and improving environmental quality (Wen et al., 2022).

Consequently, the extent of regional environmental governance substantially impacts the regional sector's evolution. It plays a pivotal role in mitigating carbon emissions in the context of copper extraction through scientific and technological frameworks.

Based on the analysis of how Industry 4.0, economic development, and environmental regulation can strengthen or weaken the S&TF–emissions reduction link, this paper proposes the third research hypothesis:

H3. Factors such as the level of local Industry 4.0 development, economic progress, and environmental regulations act as moderators in reducing carbon emissions from copper mining through technology and finance.

Study design

Modeling

Benchmark regression model

In this paper, we employ a benchmark regression model to examine the influence of S&TF on carbon productivity across various Chinese provinces. The model equation is presented as follows: Eq. (1):

$$CECM_{it} = \alpha_0 + \alpha_1 Sfin_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), $CECM_{it}$ is the level of carbon emissions from copper mining in province i in year t, $Tfin_{it}$ is the level of S&T financial development in province i in year t, X_{it} is a control variable, μ_i is a province fixed effect, λ_t is a year fixed effect, and ε_{it} denotes the error term.

Threshold regression models

To examine the dynamic effect of S&TF affecting carbon emissions from copper mining, we establish a threshold regression model, with S&TF serving as the threshold variable. The model expression is depicted in Eq. (2):

$$CECM_{it} = \eta_1 Sfin_{it} I(Sfin_{it} \le \gamma_1) + \eta_2 Sfin_{it} I(Sfin_{it} > \gamma_1) + \eta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Given the possible existence of multiple thresholds, Eq. (2) is extended to further construct a multi-threshold regression model with the expression shown in (3):

$$\begin{aligned} CECM_{it} &= \lambda_1 Sfin_{it} I(Sfin_{it} \le \gamma_1) + \lambda_2 Sfin_{it} I(Sfin_{it} > \gamma_1) + \dots \\ &\lambda_n Sfin_{it} I(Sfin_{it} \le \gamma_n) + \lambda_{n+1} Sfin_{it} I(Sfin_{it} > \gamma_n) + \lambda X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{3}$$

Finally, the variables of industry 4.0 development level (Dli4.0), economic development level (Ed), and environmental regulation (Er) are introduced into the model (3) to examine the heterogeneous adjustment mechanism of S&TF on carbon productivity, as shown in Eqs. (4), (5), and (6):

$$\begin{aligned} CECM_{it} &= \alpha_1 Sfin_{it} I(Dli4.0_{it} \le \gamma_1) + \alpha_2 Sfin_{it} I(Dli4.0_{it} > \gamma_1) + \dots \\ &\alpha_n Sfin_{it} I(Dli4.0_{it} \le \gamma_n) + \alpha_{n+1} Sfin_{it} I(Dli4.0_{it} > \gamma_n) + \lambda X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} CECM_{it} &= \alpha_1 Sfin_{it} I(Ed_{it} \le \gamma_1) + \alpha_2 Sfin_{it} I(Ed_{it} > \gamma_1) + \dots \\ &\alpha_n Sfin_{it} I(Ed_{it} \le \gamma_n) + \alpha_{n+1} Sfin_{it} I(Ed_{it} > \gamma_n) + \lambda X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} CECM_{it} &= \alpha_1 Sfin_{it} I(Er_{it} \le \gamma_1) + \alpha_2 Sfin_{it} I(Er_{it} > \gamma_1) + \dots \\ &\alpha_n Sfin_{it} I(Er_{it} \le \gamma_n) + \alpha_{n+1} Sfin_{it} I(Er_{it} > \gamma_n) + \lambda X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{6}$$

Variables' selection

Explained variables

Carbon emissions from copper mining (CECM) are a critical concern, yet annual direct access to data on fossil energy consumption during copper mining across Chinese provinces remains elusive. Therefore, we rely on the methodology outlined by Shi (2022) to estimate carbon emissions. By referencing statistical data on copper ore consumption and energy usage from the Yearbook of China Non-Ferrous Metals Industry, we calculate the physical amount of various fossil energies required per ton of copper ore mining. This calculation is then multiplied by each province's annual copper ore production, yielding the physical amount of fossil energy consumed in copper ore mining for each province. Multiplying this by the corresponding carbon emission factor, drawn from the IPCC and based on the study by Wang et al. (2023), allows us to calculate carbon dioxide emissions from copper ore mining in different provinces during the study period. Our analysis, detailed in Table 1, reveals a declining trend in fossil energy consumption per ton of copper ore mined over time. This trend may be attributed to mining enterprises

Table 1
Physical fossil energy consumption per ton of copper ore mined, 2011–2020.

vintages	Coal/ t	Coke/ t	Diesel/ t	Gasoline/ t	Natural gas/10 m43	Electricity/ 10^4 kwh
2011	6.978	1.246	1.991	0.429	0.171	12.324
2012	7.198	1.126	1.733	0.340	0.194	12.479
2013	5.531	0.680	1.698	0.217	0.153	11.992
2014	4.505	0.636	1.197	0.157	0.078	10.040
2015	4.054	0.474	0.911	0.134	0.037	8.651
2016	3.808	0.420	0.798	0.126	0.053	7.514
2017	3.114	0.302	0.674	0.110	0.048	6.699
2018	3.192	0.468	0.716	0.101	0.030	7.352
2019	2.159	0.399	0.440	0.085	0.032	7.155
2020	2.435	0.091	0.297	0.083	0.035	6.475

adopting advanced technology and equipment.

Our carbon emissions calculation considers six fossil energy sources: coal, coke, gasoline, diesel, natural gas, and electricity, each with its respective carbon emission coefficients provided by the IPCC. The method of calculation is illustrated in Eq. (7):

$$CO_2 = \sum_{i=1}^{8} CO_{2i} = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times R \tag{7}$$

In Eq. (7), CO_{2i} is the carbon dioxide emission of the *ith fossil* energy source, E_i is the consumption of the *ith fossil* energy source, NCV_i is the average low-level heat generation of the *ith fossil* energy source, CEF_i is the carbon emission factor of the *ith fossil* energy source; COF_i is the carbon oxidation factor of the *ith* fossil energy source, and R is the ratio of relative molecular weight of carbon dioxide to carbon.

Core explanatory variables

Technology for finance (Tfin): Drawing on the study of Fang and Zhang (2023), this paper posits that S&T functions as a dynamic equilibrium system shaped by interactions among financial institutions, government entities, technology enterprises, and external factors. Following the approaches of Zhang and Su (2022) and Liu and Liu (2022), we assess the S&T financial ecosystem of Chinese provinces across five dimensions: S&T support capacity, government backing, financial development, financial openness, and digital inclusive finance.

Using factor analysis, we construct the S&T financial development index for Chinese provinces from 2011 to 2021. This method condenses numerous indicators into a smaller set while preserving the essence of the original variables, thereby capturing their correlations (Li et al., 2020). The analysis extracts two common factors through principal component analysis, with a cumulative variance contribution rate of 94.876 %. The factor scores of these two components are then weighted and aggregated to generate the S&TF index. Table 2 presents the S&TF ecosystem indicators.

Table 2
Science and technology finance ecosystem.

Type of indicator	Primary indicators	Secondary indicators
Technology and Financial Ecology	Scientific and technical support capacity	Employment in scientific research and employment services
		Provincial S&T expenditures
	Government support capacity	Government expenditure on S&T
	Level of financial development	Value added of the financial sector
	Financial openness	Provincial direct outward investment
	Level of inclusive financial development	Digital financial inclusion indicators

Threshold variables

We explore the nonlinear effect of S&TF on carbon emissions from copper mining, with S&TFs serving as the threshold variable. Secondly, we consider the level of Industry 4.0 development (Dli4.0), economic development (Ed), and environmental regulation (Er) as threshold variables. The logarithmic value of GDP per capita gauges economic growth. At the same time, environmental regulation is represented by the ratio of completed investment in the province's industrial pollution control program to GDP.

Measuring the level of Industry 4.0 development is complex, as scholars have not yet agreed on a standardized method. Industry 4.0 involves integrating and upgrading industrial manufacturing through advanced information technologies such as artificial intelligence (AI) and the Internet of Things (IoT). These technologies create new opportunities for the growth and transformation of the manufacturing sector. Following the approaches of Lv et al. (2021) and Li and Zhang (2021), this study measures Industry 4.0 development across Chinese provinces using a set of indicators that capture different aspects of intelligent technology development:

- **Artificial intelligence development level**: measured by the number of AI enterprises in each province, with data obtained from the Tian-eye check system.
- **Infrastructure investment**: based on fixed asset investment in information transmission, computer services, and the software industry.
- **Software product revenue**: including revenue from basic, application, and support software.
- **Embedded system revenue**: reflecting the extent of integration of intelligent technologies into other industries, particularly in areas such as smart transportation, healthcare, and device identification.
- **Innovation capability**: measured by the application of AI patent technology, with data sourced from the State Intellectual Property Office using AI patent classification numbers.

To construct the Industry 4.0 development index, this study applies factor analysis, similar to the procedure used for the S&TF index. Principal component analysis extracts two common factors from the above indicators, yielding a cumulative variance contribution rate of 86.347 %. The scores of these common factors are then weighted to generate a comprehensive index of Industry 4.0 development. The threshold variable index system is detailed in Table 3.

Control variables

To effectively gauge the impact of S&TF on carbon emissions from copper mining, we reference the studies by Wang (2021) and Dai et al. (2022) and include the following control variables: industrial structure (Ins), internet penetration rate (Inp), urbanization level (Ur), population density (Pd), and trade openness level (Tro).

Industrial structure (Ins) is quantified by the ratio of value added from the tertiary industry to value added from the secondary sector.

Table 3
Indicator system for threshold variables.

Type of indicator	Indicator name	calculation method
Threshold variables	Industry 4.0 development level	Level of development of artificial intelligence
		Infrastructure inputs
		Software product inputs
		Embedded system inputs
		Innovation capacity
	Level of economic development	Logarithmic value of regional GDP per capita
	environmental regulation	Investment in industrial pollution project management/GDP

Internet penetration rate (Inp) is determined by the ratio of the number of Internet access terminals to the local population.

Urbanization level (Ur) is assessed by the proportion of the urban population in the province to the resident population.

Population density (Pd) is measured by the number of residents per square kilometer.

The total regional imports and exports to GDP ratio calculates the trade openness level (Tro).

Data sources

To ensure the amalgamation of timely, available, and reliable data, this study focuses on 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2011 to 2020. Data on carbon emissions from copper mining are sourced from the China Nonferrous Metals Industry Yearbook, while core explanatory variables related to S&TFare obtained from the China Energy Statistical Yearbook, the National Bureau of Statistics, and the Digital Finance Research Center of Peking University. Threshold variable data are gathered from the China Electronic Information Industry Statistical Yearbook, the Eyeball Search System, the State Intellectual Property Office, and the China Environmental Statistical Yearbook. Control variable data are sourced from the China Statistical Yearbook and the National Bureau of Statistics. In instances of missing data, interpolation techniques are employed. Interpolation was chosen since the dataset includes continuous annual provincial-level indicators, in which the gaps in the data usually involve one or two years of missing values instead of long gaps. Linear interpolation, in this case, maintains the data's time continuity but does not cause sharp discontinuities in the time series.

Descriptive statistics for each variable are presented in Table 4.

Results and discussion

Benchmark regression

The Hausman test on the benchmark model yields a Chi-square value of 22.53 with a corresponding p-value of 0.0948. This result rejects the null hypothesis in favor of the fixed-effects specification. Accordingly, this paper employs a panel fixed-effects model (individual and time double-fixed) for regression estimation, applying cluster-robust standard errors to address potential biases arising from heteroskedasticity and autocorrelation.

To capture the time-varying effects of S&TF on carbon emissions from copper mining and to mitigate potential endogeneity concerns related to reverse causality, the approach of Li et al. (2022) is adopted. Specifically, both the current value (Tfin) and the one-period lagged value (L.Tfin) of the S&TF variables are included as core explanatory variables in the model estimation.

The estimation results are reported in Table 5. Columns (1) and (3) present simple regressions without control variables, while columns (2) and (4) incorporate control variables. Across all specifications, the regression coefficient of S&TF is negative and statistically significant at the 1 % level, indicating its strong effect in reducing carbon emissions from copper mining. When control variables are introduced, the absolute value of the S&TF coefficient decreases. This reduction may reflect the complexity of emission reduction, as omitting other relevant variables could lead to an overestimation of the effect of S&TF.

Table 5
Benchmark regression results.

	(1) CECM	(2) CECM	(3) CECM	(4) CECM
Tfin	−1.834***	−1.646***		
	(0.383)	(0.448)		
L. Tfin			−1.930***	−1.797***
			(0.428)	(0.488)
Ins		−0.328**		−0.447*
		(0.235)		(0.254)
Inp		−0.861*		−0.932*
		(0.513)		(0.551)
Ur		−1.116		−2.837
		(2.274)		(2.430)
Pd		−0.114		−0.130
		(0.179)		(0.192)
Tro		0.747		1.062
		(0.579)		(0.670)
Province Effects	Fixed	Fixed	Fixed	Fixed
Time Effects	Fixed	Fixed	Fixed	Fixed
N	300	300	300	300
R^2	0.219	0.194	0.190	0.218

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Compared with the current regression coefficient of S&TF, the absolute value of the coefficient for the lagged-period variable of S&TF is notably larger. This suggests a delayed effect, with the influence of S&TF on carbon emissions from copper mining strengthening over time. To sustain these benefits, continuous investment in S&TF is essential (Wang & Gu, 2021). Integrating emerging technologies such as big data, cloud computing, and blockchain into traditional finance enhances the accessibility of financial services for mining enterprises. It supports more efficient regional capital flows (Lei et al., 2023).

Promoting the utilization of resource-intensive production techniques by local mining businesses may enhance the efficiency of resource distribution within the area and reduce carbon emissions (Chang, 2022).

In sum, the regression results preliminarily confirm that S&TF plays a pivotal role in reducing carbon emissions in the copper mining process across various provinces in China.

Robustness tests

To ensure the robustness of the benchmark regression results, this paper conducts a thorough robustness test by employing three approaches: replacing the econometric model, substituting the core explanatory variable measure, and altering the sample data interval.

Table 4
Descriptive statistics of variables.

Variable type	variant	sample size	average value	standard deviation	minimum value	maximum values
Explanatory variable	CECM	300	0.658	0.764	0.000	2.658
Core explanatory variables	Tfin	300	0.457	0.652	0.011	3.932
Threshold variables	Id	300	0.903	1.108	3.565	8.805
	Dli4.0	300	0.214	0.348	0.480	3.118
	Er	300	1.983	2.704	1.602	16.416
Control variable	Ins	300	8.082	12.376	0.086	110.339
	Inp	300	0.411	0.729	0.527	5.244
	Ur	300	0.185	0.218	0.096	0.986
	Pd	300	0.094	0.122	0.350	0.896
	Tro	300	0.333	0.407	6.639	8.669

1. Replacement of the econometric model: In addition to utilizing the double fixed-effects model to investigate the correlation between S&TF and carbon emissions from copper mining, this paper employs the generalized least squares (GLS) method for estimation. The estimation results are presented in column (1) of Table 6. Notably, after replacing the econometric model, the direction and significance of the coefficients for S&TF remain consistent with those in the baseline model. This demonstrates the robustness of the results and indicates that the model is not affected by serious heteroskedasticity problems.
2. Replacement of core explanatory variable measurement: In addition to modifying the measurement model, this paper investigates the baseline regression outcomes by altering the measurement approach for the explanatory variables. Since some samples in the explanatory variable dataset contain zero values, this paper applies a logarithmic transformation to the explanatory variables after adding 1. This adjustment provides a new indicator for measuring carbon emissions in the copper mining process. The regression results, reported in column (2) of Table 6, show that even under this alternative measurement approach, S&TF significantly reduces carbon emissions in copper mining.
3. Replacement of the sample data interval: To reduce the potential impact of outliers on the regression results, this paper applies a 5 % data trimming procedure. Following this adjustment, the regression is re-estimated using interval regression, as shown in column (3) of Table 6. A comparison with the benchmark results indicates that the magnitude and significance of the S&TF coefficient remain largely consistent, confirming the robustness of the findings.

A series of robustness tests confirms that S&TF effectively diminishes the level of carbon emissions in the copper mining process across Chinese provinces. These findings underscore the robustness of the benchmark regression results.

Analysis of the threshold effect of technology finance on carbon productivity

To delve deeper into whether there exists a threshold effect regarding the impact of S&TF on carbon emissions from copper mining, this paper employs the multiple threshold self-sampling method for testing, with the results presented in Table 7. It is evident that at the national level, S&TF demonstrates a significant single-threshold effect.

Furthermore, the paper conducts a robustness test of the threshold effect by lagging the S&T variable by one period to mitigate the endogeneity problem resulting from reverse causality. The findings reveal a significant threshold effect of S&TF at the national level. However, the *p*-value of the double threshold effect is 0.500, failing to meet the significance level test criteria. This suggests the presence of a threshold in reducing the level of carbon emissions in the copper mining process, indicating variations in the effectiveness of S&TF across different developmental stages.

In summary, this paper opts for a single threshold model to examine the nonlinear effect of S&TF on the impact of carbon emissions from copper mining.

Table 7
Threshold test results.

Area	Number of thresholds	Estimated value	F-value	*p*-value	Number of BS
nationwide	single threshold	0.176***	16.18	0.000	300
	double threshold	0.669	11.49	0.500	300
robustness check	single threshold	0.151**	8.79	0.033	300
	double threshold	0.459	5.10	0.200	300
eastern part	single threshold	0.318***	18.51	0.000	300
	double threshold	0.440**	6.57	0.033	300
	triple threshold	0.512	6.64	0.400	300
Central Region	single threshold	0.440*	20.97	0.067	300
	double threshold	0.569	8.89	0.300	300
western region	single threshold	0.440**	14.44	0.067	300
	double threshold	0.569	10.19	0.267	300

Note: *p*-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The regression results of the threshold effect of S&TF on carbon emissions from copper mining are illustrated in Table 8, where the first and second columns represent the regression outcomes for the current and lagged values of the S&TF variables, respectively. By integrating the findings from Table 7, it becomes apparent that on a national scale, a threshold value of 0.163 exists for the level of S&T financial input.

When the level of S&T financial input falls below 0.163, the regression coefficient of S&TF stands at −1.610 and achieves statistical significance at the 1 % level. This indicates that at this juncture, S&TF effectively reduces the level of carbon emissions in the copper mining process. Conversely, when the input level of S&TFs surpasses 0.163, the regression coefficient of S&TF amounts to −2.774 and remains statistically significant at the 1 % level. This suggests that at this input level, S&TF exerts a substantially more suppressive effect on the carbon emissions associated with copper mining.

Likewise, in the robustness test, upon examining the results of column (2) in both Tables 7 and 8, it is evident that although the two thresholds of S&TF and the regression coefficients of S&TF under different input levels change following the lagging of the S&TF index by one period, the observed dynamic enhancement trend in the inhibition effect of S&TF on the carbon emissions of copper mining persists. This

Table 6
Robustness test.

	(1) CECM	(2) CECM	(3) CECM
Tfin	−0.681***	−1.072**	−1.243**
	(0.167)	(0.531)	(1.566)
Control variables	YES	YES	YES
Province Effects	Fixed	Fixed	Fixed
Time Effects	Fixed	Fixed	Fixed
N	300	300	300
R^2	0.531	0.770	0.569

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8
Regression results based on the threshold model.

variant	nationwide		the east	central section	western part
	(1)	(2)			
Tfin_1	−1.610***	−1.738***	−1.083**	−1.476**	−0.703*
	(0.430)	(0.464)	(0.543)	(1.170)	(1.820)
Tfin_2	−2.774***	−2.998***	−3.409***	−2.498*	−2.458
	(0.562)	(0.606)	(0.757)	(1.426)	(1.971)
Tfin_3			−5.202***		
			(1.075)		
Control variables	YES	YES	YES	YES	YES
Province Effects	Fixed	Fixed	Fixed	Fixed	Fixed
Time Effects	Fixed	Fixed	Fixed	Fixed	Fixed
N	300	300	300	300	300
R^2	0.420	0.392	0.574	0.605	0.367

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

underscores the robustness of the conclusion, thereby validating hypothesis H2.

Spatial heterogeneity analysis of technology finance on carbon productivity

To explore regional disparities in the impact of S&TF on carbon emissions from copper mining, this study categorizes the 30 sample provinces and cities in China into three major economic regions: East, Central, and West (Zhang, 2010). Subsequently, the spatial effect of S&TF on copper mining carbon emissions is further scrutinized from a spatial perspective.

The regression results presented in Tables 7 and 8 highlight a notable difference in the effect of S&TF on carbon emissions from copper mining across China's three major economic regions. The outcomes of the threshold test suggest that the eastern provinces and areas of China warrant examination using the dual threshold model. China's central provinces and regions should be analyzed using the single threshold model. China's western provinces and territories should be assessed using the single threshold model.

In summary, the findings for eastern China reveal two thresholds of S&TF at 0.318 and 0.440, respectively. When the intensity of S&TF falls below 0.318, the regression coefficient is −1.083 and significant, suggesting that S&TF development can reduce carbon emissions in copper mining. As the S&TF input reaches between 0.318 and 0.440, the coefficient becomes −3.409 and significant, indicating an enhanced inhibition effect post the first threshold. Beyond 0.856, the coefficient drops to −5.202 and remains substantial, signifying the peak inhibition effect of S&T finance.

On the other hand, for central China, the threshold value of S&TF stands at 0.440. When the input level is below this threshold, the regression coefficient is −1.476 and significant, showing a substantial inhibition of carbon emissions from regional copper mining. Once the S&T finance surpasses the threshold of 0.440, the coefficient decreases to −2.498 and remains significant, suggesting a further enhancement in the inhibitory effect of S&T finance.

In China's Western region, the threshold value for technology finance is 0.162. When the intensity of S&TF falls below 0.162, the model's regression coefficient stands at −0.703 and is significant. This indicates that S&TF can effectively reduce carbon emissions from copper mining. However, when the intensity of S&TF exceeds 0.162, the regression coefficient drops to −2.548, although it loses significance.

Overall, compared to the eastern region, the impact of S&TF development on suppressing carbon emissions from copper mining in the central and western areas appears weaker. This discrepancy may be attributed to substantial differences in the development status among the three major regions of eastern, central, and western China. The east region hosts most economically developed cities like Beijing and Shanghai, benefiting from geographical advantages such as coastal access and resource abundance. Moreover, the eastern region boasts a higher level of S&TF development, facilitating the establishment of low-carbon industries and the advancement of low-carbon energy sources (Kong, 2022). Conversely, the central and western areas face challenges in S&T infrastructure development, immature S&T markets, and a lower level of S&TF development. These factors hinder realizing energy consumption structure transformation and reducing carbon emissions in these regions (Li et al., 2022).

In the three major economic regions of East, Central, and West China, while variations exist in the threshold value and the impact of S&TF on copper mining carbon emissions across different economic regions, overall, the inhibitory effect of S&TF follows a nonlinear pattern of increasing marginal effect. This observation further confirms the hypothesis H2.

Analysis of the regulatory mechanism of S&TF on carbon emissions from copper mining

When regressing S&TF as a threshold variable, we observe a shift in its impact on copper mining carbon emissions from low to high, which is evident nationally and within the three major economic zones of East, Central, and West China. However, a pertinent question arises: Does increasing the level of S&T financial investment inevitably lead to a reduction in copper mining carbon emissions? If so, then augmenting the intensity of S&TF could potentially maximize its impact. Conversely, if this assumption doesn't hold, escalating S&TF inputs might result in regional resource mismatches, leading to inefficiencies in the copper mining process and subsequently higher carbon emissions.

To delve deeper into whether other factors moderate the relationship between S&TF and copper mining carbon emissions, this study introduces three variables: the level of Industry 4.0 development, economic development, and environmental regulation. These factors are analyzed for their heterogeneous moderating effects. Threshold test results in Table 9 reveal two thresholds for the level of Industry 4.0 development, one threshold for economic development, and another for environmental regulation. These thresholds are examined using the panel threshold model, with empirical findings detailed in Table 10.

The results in Table 10 reveal a heterogeneous constraining mechanism affecting the impact of S&TF on carbon emissions from copper mining.

In column (1) of Table 10, where the development level of Industry 4.0 serves as the threshold variable, combined with the findings from Table 9, it's evident that Industry 4.0 development exhibits two thresholds at 2.092 and 3.107. When the Industry 4.0 development level falls below 2.092, the regression coefficient of S&T stands at −1.954 and is significant. Here, S&TF significantly reduces carbon emissions from copper mining. As the Industry 4.0 development level ranges between 2.092 and 3.107, the regression coefficient diminishes to −0.467, indicating a weakened inhibitory effect of S&TF. Finally, when the industry 4.0 development level exceeds 3.107, the model's regression coefficient reaches −3.360 and is significant, marking the most potent inhibitory effect of S&TF. Thus, under the influence of the Industry 4.0 development level, the impact of S&TF on curbing carbon emissions from copper mining exhibits a dynamic "U-shaped" pattern.

Column (2) in Table 10 presents regression results with the level of economic development as the threshold variable. Combined with Table 9, the threshold value for economic development is determined to be 2.572. When economic development falls below this threshold, the coefficient of S&TF is −0.548 and significant. Conversely, when economic development surpasses 2.572, the regression coefficient of S&TF decreases to −0.967 but remains substantial. The moderating effect of economic development level suggests that the inhibitory effect of S&TF on copper mining carbon emissions increases with higher levels of

Table 9
Threshold test with different constraints.

Threshold variables	Number of thresholds	estimated value	F-value	*p*-value	Number of BS
Industry 4.0 development level	single threshold	2.092***	10.05	0.000	300
	double threshold	3.107***	22.31	0.000	300
	triple threshold	3.111	9.39	0.667	300
Level of economic development	single threshold	2.572*	9.24	0.067	300
	double threshold	4.863	7.26	0.567	300
environmental regulation	single threshold	17.775**	6.81	0.033	300
	double threshold	25.174	4.27	0.733	300

Table 10
Threshold effect regression results based on different constraints.

	(1) CECM	(2) CECM	(3) CECM
Tfin_1	−1.954***	−0.458***	−0.547***
	(0.133)	(0.134)	(0.363)
Tfin_2	−0.467***	−0.967**	−0.495*
	(0.857)	(0.241)	(0.137)
Tfin_3	−3.360***		
	(0.379)		
Control variables	YES	YES	YES
Province Effects	Fixed	Fixed	Fixed
Time Effects	Fixed	Fixed	Fixed
N	300	300	300
R^2	0.492	0.712	0.578

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

economic development.

In column (3) of Table 10, the regression results are shown with environmental regulation as the threshold variable. Table 9 identifies the threshold value for environmental regulation as 17.775. When environmental regulation falls below this threshold, the coefficient of S&TF is −0.547 and significant. However, when environmental regulation exceeds 17.775, the coefficient decreases to −0.495, which is still substantial. Crossing this threshold weakens the effect of S&TF in reducing carbon emissions from copper mining.

Under the influence of different variables, the impact of S&TF on carbon emissions from copper mining exhibits considerable variation. When regulated by the development level of Industry 4.0, the effect of S&TF displays a "U-shaped" pattern of change. The advent of the Industry 4.0 era has substantially elevated enterprise digital integration and innovation levels, enabling companies to tailor production plans more efficiently to reduce energy usage and consequently lower carbon emissions in copper mining regions (Yang et al., 2022). Moreover, in the Industry 4.0 landscape, companies can readily access and comprehend the latest environmental policies, fostering a shift toward more environmentally friendly mining practices and bolstering corporate environmental engagement (Tang et al., 2022).

Nevertheless, the intelligent upgrading and manufacturing process inevitably introduces more energy-efficient and eco-friendly technologies and equipment, increasing carbon emissions during the mining industry's expansion and technological enhancement phases (Sun et al., 2023). As a result, the moderating influence of the Industry 4.0 era diminishes the impact of S&TF on carbon emissions from copper mining in this timeframe. In due course, with businesses establishing stable production capacities and finalizing iterative enhancements of technological machinery, the mining sector will organically shift towards greener and more sustainable approaches, enhancing the effectiveness of S&TF in mitigating carbon emissions from copper mining. When economic development levels regulate the scenario, the promotion effect of S&TF on copper mining carbon emissions rises with economic development (Yang et al., 2022). Regional carbon emission levels are influenced by diverse factors such as economic status, resource availability, and environmental regulations. Governments tend to allocate greater investments in S&T financial ecosystems in economically developed regions, enhancing S&TF's efficacy in carbon emission reduction by attracting high-end technical talent and improving local infrastructure.

Under the influence of environmental regulations, the inhibitory effect of S&TF on carbon emissions from copper mining gradually wanes. Regional environmental regulations are closely linked to economic development levels (Xu et al., 2022). However, stringent environmental regulations may challenge energy-intensive mining enterprises to balance environmental concerns with business performance, potentially prompting them to relocate to neighboring regions to circumvent excessive regulations (Hu et al., 2022).

Conclusions and recommendations

Industry 4.0 propels the mining industry's transformation towards digitalization and intelligence, bolstering its core competitiveness by accelerating old and new energy transformation. Focusing on China's copper mining industry across 30 provinces, this study scrutinizes the nonlinear impact of S&TF development on copper mining carbon emissions. It further delineates the heterogeneous constraining effect of S&TF on carbon emissions from copper mining. Leveraging panel data from 2011 to 2020, the analysis unfolds through the double fixed-effect and multi-threshold regression models to explore the regional variations in S&TF's impact on carbon emissions from copper mining.

The key findings are: First, S&TF significantly diminishes regional carbon emissions in the copper mining process, a conclusion reaffirmed through robustness testing. Second, the impact of S&TF on reducing carbon emissions from copper mining exhibits a positive law of increasing marginal effect. Third, regional heterogeneity exists in S&TF's role in curbing carbon emissions from copper mining, with a more substantial impact observed in China's eastern region compared to the central and western areas. Fourth, the levels of Industry 4.0 development, economic development, and environmental regulation modulate S&TF's impact on carbon emissions from copper mining. Under Industry 4.0 development level constraints, S&TF's inhibitory effect initially decreases before rising in a "U"-shaped dynamic change pattern. Enhanced economic development amplifies S&TF's inhibitory effect, while heightened environmental regulation weakens it.

Based on these conclusions, the study proposes the following policy insights: Firstly, enhance the ecological environment of S&TF to maximize its inhibitory effect on carbon emissions from copper mining, as the results confirm that S&TF directly reduces carbon emissions. Provinces should bolster investment and guidance in S&T innovation, strengthen scientific and technological financial infrastructure, and promote energy efficiency through scientific and technological finance development. Secondly, differentiated S&T financial support policies should be formulated to suit the unique characteristics of China's eastern, central, and western regions, as the heterogeneity analysis demonstrates that the influence of S&TF varies across regions. Third, efforts should focus on enhancing regional intelligence levels, economic development, and environmental regulations to strengthen the inhibitory effect of S&TF on carbon emissions from copper mining, as the moderating effect analysis shows that these factors amplify the inhibitory role of S&TF on carbon emissions. This requires adequate investment in S&TF, increasing financial support for its development in central and western regions, and fostering stronger linkages between S&TF and environmental regulations to promote green and high-quality growth in the mining sector.

Funding

This paper is supported by "Research on the Dynamic Value Evaluation of Agricultural Biological Assets, Mortgage Financing Model and Risk Management Policy," National Natural Science Foundation of China (NSFC), Jan 2023 -Dec 2026, No. 72273105. Sponsor and host: Jianchao Luo. This paper is also supported by "Research on the Effectiveness Evaluation, Risk Control and System Construction of the Agricultural Credit Guarantee Policy," National Natural Science Foundation of China (NSFC), Jan 2019 -Dec 2022, No. 71873100. Sponsor and host: Jianchao Luo. This paper is also supported by the Chinese Universities Scientific Fund, No. 2452025179, "Research on the Institutional Design and Practical Pathways of Inclusive Finance in Promoting Common Prosperity," July 2025 -December 2025. Sponsor and host: Jianchao Luo. This paper is also supported by "Research on the Policy Orientation and Implementation Path of Financial Empowerment of Rural Revitalization," the Soft Science Project of the Central Agricultural Office and the Rural Revitalization Expert Advisory Committee of the Ministry of Agriculture and Rural Affairs, May 2022 -May 2023, No. rkx20221801. Sponsor and host: Jianchao Luo.

CRediT authorship contribution statement

Arshad Ahmad Khan: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Sufyan Ullah Khan:** Writing – review & editing, Software, Formal analysis. **Muhammad Abu Sufyan Ali:** Writing – review & editing, Visualization, Software. **Ijlal Haider:** Writing – review & editing. **Jianchao Luo:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare no conflict of interest.

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